臺灣大學經濟系

經濟計量數值方法導論

上 課 時 間 ： 星期一，第 7–8 節.
上 課 地 點 ： 社科大樓 306 教室
授 課 老 師 ： 王泓仁　教授，wangh@ntu.edu.tw
研　究　室 ：社科大樓 824 室
課 程 網 頁 ： https://cool.ntu.edu.tw/courses/34662
助　　　教 ： 張豐瑾 r11323032@ntu.edu.tw

一、 課程概述 Course Description

This course provides an introduction to fundamental numerical methods frequently utilized in econometrics, quantitative social science, and data science. It covers topics such as random sampling, numerical integration, numerical differentiation, optimization, simulation, and maximum likelihood estimations. While the theoretical aspects are presented in an accessible manner, the emphasis is placed on practical application.

A key component of the course is teaching computer programming through Julia. Students will learn to code functions that implement the numerical methods discussed, with practical exercises designed to enhance their coding proficiency. Mastery of numerical methods and the development of programming skills are viewed as interconnected, each reinforcing the other.

As a two-credit course, it does not aim to offer exhaustive instruction in advanced numerical or programming techniques. Instead, its goal is to establish a robust foundation, empowering students to confidently address computational problems by sharpening their coding and problem-solving abilities.
The course features video-based lectures, complemented by weekly homework assignments. Biweekly in-person classes are scheduled for discussions on homework and to address any questions related to the lectures..

二、 教學目標 Course Objective

Upon completion of this course, students will be able to:

1. grasp basic theories of essential numerical methods;
2. obtain programming skills in modern computer languages;
3. code numerical algorithms and methods to solve empirical problems; and
4. teach themselves to code in other languages in the future.

三、 每週進度及教學內容簡述 Course outline (Course Schedule of 16 weeks)

Week 1: introduction and Julia setup

- Explain the course format and purpose to students.
- Introduce Julia: What is it, the potential for scientific computing, and why is it good for classroom learning. Help students to set up Julia environments in computers.

Week 2: random, pseudo-random, and quasi-random numbers

- Introduce various types of random numbers; how to draw random numbers for different needs; random number vs. random number generators (RNG) and how to use RNG to ensure re-reproducibility (in both of the local and global scopes). Introduce basic syntax and matrix operations of Julia.

Week 3: Inverse Transform Sampling

- Sampling methods allow for inferences about large populations from smaller subsets, enhancing study feasibility and efficiency. The inverse transform method is key for generating random samples based on a distribution's cumulative function, enabling complex model simulations.

Week 4: Rejection Sampling

- Rejection sampling is crucial for sampling from complex distributions when direct methods fail, facilitating statistical simulations and analyses.

Week 5: Gibbs Sampling

- Gibbs sampling is useful for estimating the joint distribution of multiple variables, especially in high-dimensional spaces where direct sampling is infeasible. It is crucial for Bayesian inference and statistical modeling.

Week 6: Integration: Quadratures

- The method numerically approximates the integrals of functions, especially when analytical solutions are difficult or impossible to obtain. We introduce the basic theory of quadrature methods, including the midpoint method, the trapezoidal method, the Simpson’s rule, and various Gaussian quadrature rules (Gauss-Legendre, Gauss-Hermite, Gauss-Laguerre).

Week 7: Integration: Monte Carlo Methods

- The methods use random sampling to approximate the value of the integral. They are particularly helpful for high-dimensional integration problems.

Week 8: Integration: Quasi-Monte Carlo Methods

- Quasi-Monte Carlo integration methods enhance the Monte Carlo approach by using low-discrepancy sequences instead of random sampling, significantly improving the accuracy and convergence rate of the integral estimation.

Week 9: Numerical Finite Differentiation

- Numerical finite differentiation is key for estimating derivatives when analytical methods are not feasible, enabling the analysis of rates of change and gradients in physical systems and technical applications. We introduce the basic theory of the method and discuss various issues that affect numerical accuracy.

Week 10: Automatic Differentiation

- Automatic differentiation is vital for accurately and efficiently calculating derivatives, crucial for optimization and machine learning. It overcomes the limitations of numerical and symbolic differentiation, enhancing precision in training neural networks and solving complex systems.

Week 11: Root Finding

- Root finding methods are crucial for solving equations by identifying where functions equal zero, essential for modeling and analyzing real-world systems where analytical solutions are not available.
- Introduce the gradient-free methods, including Nelder-Mead and the simulated annealing.
- Introduce the methods based on the 1st-order gradients, including the gradient descent and BFGS.

Week 12: Optimization

- Optimization methods are essential for finding the best solutions to complex problems. They are widely used in econometrics including the maximum likelihood estimations. We introduce methods based on the 1st-order gradients, including the gradient descent and BFGS, and methods based on the 2^{nd}-order Hessian, including the Newton method and other quasi-Newton methods.

Week 13: Maximum Likelihood Estimation

- Introduce the basic theory of MLE and how different optimization methods may apply to the estimation.
- Discuss the initial value problem and the convergence problem in general. Discuss robust estimates of variance.

Week 14: Maximum Simulated Likelihood Estimation

- MSLE is crucial for estimating parameters of models where traditional likelihood functions are intractable. It uses simulation to approximate the likelihood, allowing for the analysis of complex models in economics, finance, and other fields.

Week 15-16: Review and the Final Project

四、 作業、考試、及評分 Homework, Exams, and Grading

- 原則上每週都有作業，需在規定時限（通常一星期）內上傳。
- 最低分的兩次作業成績不列入計算，所以不接受任何遲交、補交、或不交作

業的理由。

- 為鼓勵社群式學習（community-based learning），此課程要求每位學生需在網頁討論區發言（發問、討論、解答，都算）至少四次。未滿四次將無法獲得討論分數（8 分）。
- 總成績計算方式：課堂及網路討論（8%），作業（52%），期末計畫（40%）。

五、 閱讀材料 Reading

Cameron, A.C. and Trivedi, P.K. (2005) Microeconometrics: Methods and Applications, Cambridge University Press, London.

Judd, K. (1998) Numerical Methods in Economics, MIT Press, Cambridge.

Kochenderfer, M.J., and Wheeler, T.A. (2019) Algorithms for Optimization, MIT Press, Cambridge.

Koziel and Yang (2011) Computational Optimization Methods and Algorithms, Springer, New York. (free download from NTU)

Miranda, M.J., and Fackler, P.L. (2004) Applied Computational Economics and Finance, MIT Press, Cambridge.

Nazarathy and Klog (2021) Statistics with Julia, Springer, New York. (free download from NTU)

六、 其它事項 Others

1. 寫同學們寫電子郵件給我和助教時，請務必註明你的名字。
2. 電子郵件是課程正式的公告工具，請務必定時察看。
3. 課程問題請盡量在課程網頁討論區發問。若需私下聯絡我，以 Line 最即時、方便。我的 Line ID：wanghungjen99。
4. 全班學期分數太低或太高時，有可能全班調整分數。