**Economics 285E: Advanced Econometrics I**
Spring 2019

**Instructor:** Tae-Hwy Lee
**Office hours:** TR 1-2 pm, or by appointment on MWF, SPR 3103
**Lecture:** TR 2:10-3:30 pm, SPR 4128

**Course Requirement and Grading:** The course grade will be based on the many homework problems raised during the lectures and a research paper. All submissions of the homeworks and paper should be typed and submitted electronically via email. Please name the PDF file as Econ285e_HW#_your_name.pdf or Econ285e_Paper#_your_name.pdf

1. Homeworks (35%) on problems raised during the lectures. There will be 7 homeworks with each carrying 5% regardless of the length. You will have one week (7 days) for each homework.
2. Paper (35%) and presentation (30%) can be theoretical, applied, empirical, Monte Carlo, or a literature review on a specific topic. It must be related to this course. No part should be or have been used for any other term papers for other courses.
   a. Version 1 (5%) for the paper will be due by May 26,
   b. Version 2 (10%) due by June 2,
   c. Version 3 (20%) the final version due by June 16, and
   d. Presentation (30%), 20 minutes, Week 10, June 4 and 6.

## Course Outline

## I. Forecasting and Predicition

Lecture 1. Loss functions and convex optimization
*References:* Koenker and Bassett (1978), Newey and Powell (1987), Kuan et al (2009), Xie et al (2014), Diks, Panchenko, and van Dijk (2011), Diebold and Shin (2015), Chu, Lee, and Ullah (2019), Efron and Hastie (2016 Chapter 8), Rossi and Timmermann (2015), Bartlett, Jordan, and Mcauliffe (2006), Boyd and Vandenberghe (2004)

Lecture 2. GMM Estimation of the loss functions
*References:* Elliott, Komunjer, and Timmermann (2005), Hansen and Singleton (1982)

Lecture 3. Introduction to Forecasting
*References:* Hamilton (1994)

Lecture 4. Forecast combination (for mean forecast, quantile forecasts, expectile forecasts, expected shortfall forecasts, binary forecasts and classifiers, averaging, majority vote, applications)
*References:* Bates and Granger (1969), Timmermann (2006), Lee and Yang (2006), Hastie et al (2009)

Lecture 5. Forecast evaluation and comparison (inference in predictive regression)
*References:* Diebold and Mariano (1995), West (1996), Diebold (2015), Clark and McCracken (2001, 2005, 2009), Giacomini and White (2006), Clark and West (2006, 2007), Harvey at al (1998), Chao et al (2001), Stambaugh (1999), Phillips (2014), Phillips and Lee (2013, 2014), Phillips and Chen (2014), Zhu (2012), Ge and Lee (2014, 2015), Li, Liao, and Quaedvlieg (2019), Swanson and Xiong (2018 CJE 51)

Lecture 6. Forecasting using extra information: forecasting using constraints
*References:* Lee, Tu and Ullah (2014, 2015)

Lecture 7. Forecasting using extra information: forecasting using decompositions
*References:* Anatolyev and Gospodinov (2010), Lee, Xi, and Zhang (2014)

## II. Bootstrap

Lecture 8. Asymptotic Properties of Bootstrap and Subsampling (jackknife and bootstrap, central limit theorem and Edgeworth expansions, asymptotic refinement in hypothesis testing and confidence intervals, bootstrap bias reduction, consistency of bootstrap, subsampling, wild bootstrap).
[A motivation of bootstrap will be given from the jackknife view of Tukey (1958). Then we discuss the limitation and extention of the jackknife for generalizing the idea to introduce bootstrap. We discuss how bootstrap works using asymptotic expansion. We review some basic theory of the central limit theorem and discuss the Edgeworth expansion to understand the bootstrap's ability. We also consider situations where bootstrap cannot be used. Subsampling and wild bootstrap may be discussed. We consider various applications such as bias reduction, confidence intervals, testing. The goal is to understand what bootstrap is, how it works, why it fails when it does not work, how to use it, and possible advantages of using bootstrap. Bootstrap when a parameter is on the boundary of the parameter space. Bootstrap with heavy-tailed distribution.]
*References:* Efron and Hastie (2016 Chapter 10), Hall (1992 Chapters 1-3), Horowitz (2001), Andrews (2000), Woutersen and Ham (2013), Politis and Romano, Wolf (1999). bit.ly/2PSChon

## III. High Dimensioanl Models and Machine Learning

Modern computing power and data storage is rapidly changing economics in fundamental way, with new questions and new approaches. It has already helped the economists with new economic thinking in market design, pricing, forecasting, program evaluation, causal inference, and policy design and implementation. Examples are in large social media data, census or administrative database, retail data on individual consumers, data on household finance and health care, behavioral data, experimental data, large macro and finance data, data on trade, high frequency data, individual tax data, and etc. Big data is a big opportunity to solve old and new problems in better ways. It urges the new applied economics, taking advantage of the use of data science tools for data management and data processing, and also of the use of machine learning and artificial intelligence tools for regularization and post-regularization methods for estimation and inference that necessitate the emergence of new statistical theory and algorithmic empirical analysis.

### a. Regularization

Lecture 9. Factor models (pricipal components, orthogonal functions, Stein-type shrinkage for factor models, random matrix theory)
*References:* Hastie, Tibshirani, and Friedman (2009 Chapter 3), Bai (2003), Bai and Ng (2002, 2006), Stock and Watson (2002a,b, 2006, 2012), Diebold and Li (2005), Kelly and Pruitt (2015), Cheng and Hansen (2015), Carrasco and Rossi (2016), Connor and Linton (2007), Connor, Hagmann, and Linton (2012), Fan, Liao, and Mincheva (2013), Fan, Liao, and Wang (2016), Kelly, Pruitt, and Su (2017ab), Pelger and Lettau (2017).

Lecture 10. Lasso and its cousins
*References:* Hastie, Tibshirani, and Friedman (2009 Chapter 3), Efron and Hastie (2016 Chapters 7, 16).

Lecture 11. Regularized-2SLS and Regularized-GMM
*References:* Cheng and Liao (2015), Lee and Xu (2018), Belloni, Chernozhukov, Chetverikov, Hansen, and Kato (2018 arXiv:1806.01888v2)

### b. Ensemble Methods

Lecture 12. Bootstrap Aggregating and Random Forest (bagging, asymptotic properties, Rao-Blackwellization)
*References:* Hastie, Tibshirani, and Friedman (2009 Chapters 15, 16), Efron and Hastie (2016 Chapter 17), Buhlman and Yu (2002), Lee, Ullah, and Wang (2019)

Lecture 13. Boosting and its cousins
*References:* Hastie, Tibshirani, and Friedman (2009 Chapter 11), Efron and Hastie (2016 Chapters 18, 19), Chu, Lee, and Ullah (2019), Chu, Lee, Ullah, and Wang (2019)

**c. Inference**

To be added in 2020
*References:* Papers by Whitney Newey, Max Farrell, Alex Belloni, Chris Hansen, Victor Chernozhukov, Jann Spiess, Belloni, Chernozhukov, Chetverikov, Hansen, and Kato (2018 arXiv:1806.01888v2)

**d. Covariance Matrix Estimation and Applications**

Lecture 14. Multivariate GARCH models
*References:* Hamilton (1994 Chapter 21), Tsay (2010 Chapter 3), Engle (1982), Bollerslev (1986), Engle and Kroner (1995), Engle (2002), Tse and Tsui (2002), Lee and Long (2009)

Lecture 15. High-dimensioanl conditional precision matrix (estimation, applications to forecast combination, portfolio)
*References:* Bailey, Pesaran, and Smith (2016), Fan and Lv (2016), Rossi and Timmermann (2015), Hastie, Tibshirani, and Friedman (2009 Chapter 18), Engle, Ledoit and Wolf (2019), Lee, Mao, and Ullah (2018)

**e. Deep Learning**

*next time in 2020.*

**VI. Model Selection and Model Averaging**

*if time permits.*

Model Selection (derivation of AIC and TIC, derivation of BIC, properties of AIC and BIC: AIC vs BIC, Can the strengths of AIC and BIC be shared? cross-validation: properties, cross-validation vs AIC, Mallow criterion, Inference after model selection, Post Lasso)
*References:* Hastie, Tibshirani, and Friedman (2009 Chapter 7), Yang (2005), Hansen (2009 Econ 718). Efron and Hastie (2016 Chapters 12, 14, 20).

Model Averaging (Stein estimator, shrinkage, Mallow model averaging, Bayesian model averaging, JMA; weak factor models; weak IV models; combining panel data models under weak endogeneity; weak unit root models; weakly cointegrated models with weak error correction; GMM with weakly valid moments and weakly relevant moments; weak serial correlation; weak heteroscedasticity; weak structural breaks; time varying model averaging)
*References:* Hastie, Tibshirani, and Friedman (2009 Chapter 8), many papers by Bruce Hansen (2007, 2008, 2015, 2016, 2017 ...), many papers by Xinyu Zhang, Cheng and Hansen (2015), Hansen (2009 Econ 718), Hausman (1978), Sun, Hong, Lee, Wang, and Zhang (2019)

version 5/12/2019