TIME SERIES 2023 - ASU

Professor: Hedibert Freitas Lopes

Syllabus

Course description: The main goal of the course is to make the student familiar with and able to implement univariate and multivariate modern time series models. Univariate time series models we will consider include the family of autoregressive (fractionally) integrated moving average (ARIMA) models, dynamic linear models (aka state-space) models, Markov switching models, generalized autoregressive conditionally heteroskedastic (GARCH) and stochastic volatility (SV) models. Multivariate time series models we will considere include vector autoregressive (VAR) models, factor-augmented VARs, dynamic factor models and various time-varying covariance models. The inferential approach of this course is predominantly Bayesian, so we will briefly introduce key ingredients of Bayesian inference, model selection and criticism. An introduction to the main Monte Carlo methods for Bayesian inference, such as MC integration, sampling-importance-resampling (SIR), Markov chain Monte Carlo (MCMC) and sequential MC (SMC), will also be introduced. All classroom examples and implementations as well as projects will be carried out by the open-source statistical software R.

Key topics covered will be: PART I: Basic univariate time series models: AR, MA and ARMA models; unit-root non-stationarity and long-memory processes; seasonal models. PART II: Bayesian ingredients (prior, likelihood, posterior, predictive, Bayes factor and posterior model probability); Monte Carlo (MC) methods (MC integration, sampling importance resampling (SIR)) and Markov chain Monte Carlo (MCMC) methods (Gibbs sampler and Metropolis-Hastings (MH) algorithms). PART III: More univariate time series: ARCH/GARCH models; EGARCH, GARCH-M, TGARCH; Bayesian GARCH; Bayesian inference in the local level model; Dynamic models; Stochastic volatility models. We will use MCMC as well as sequential Monte Carlo (SMC) schemes to perform batch and online posterior inference. PART IV: Multivariate time series models: Vector autoregressive (VAR) models; Large Bayesian VAR (BVAR) models, factor augmented VAR (FAVAR) models, time-varying parameter BVAR (TVP-BVAR) models, Bayesian FAVAR (BFAVAR) models; Factor models and time-varying covariance models.

Useful textbooks:

- Gamerman and Lopes (2006) MCMC: Stochastic Simulation for Bayesian Inference, 2nd Edition.
- Prado, Ferreira and West (2021) Time Series: Modeling, Computation & Inference, 2nd Edition.
- Shumway and Stoffer (2011) Time Series Analysis and Its Applications with R Examples, 3rd Edition.
- Tsay (2010) Analysis of Financial Time Series, 3rd Edition.
- Tsay (2014) Multivariate Time Series Analysis with R and Financial Applications. Wiley. http://faculty.chicagobooth.edu/ruey.tsay/teaching/mtsbk

Homework assignments: **HW1** - **HW2** - **HW3:** Fit Gaussian and Student's t GARCH(1,1) to your favorite returns (Coke, Apple, Amazon, S&P, etc) using the R packages garchFit and bayesGARCH that I have used in class. Feel free to add other (non-Bayesian) GARCH-type fits based on the ARCH-glossary that we have discussed in class. Use data between January 2005 and December 2022, so you are including the 2007-2008 financial crisis, as well as the 2020-2021 COVID pandemic. Comment your findings. **HW4:** Inspired by HW3 (above), fit Gaussian and Student's t SV-AR(1) models, as well their extended versions that contemplate leverage effect (skewed effect between large positive returns and large negative returns), to your favorite returns (Coke, Apple, Amazon, S&P, etc) using the R packages stochvol (by Gregor Kastner). Use data between January 2005 and December 2022, so you are including the 2007-2008 financial crisis, as well as the 2020-2021 COVID pandemic. Comment your findings, including comparisons with the GARCH-type models from HW3. Hint: We basically perform this task in Section 5 of the following example: sv-ar(1) for S&P500 returns.

List of papers for final presentation

- Cyber risk measurement via loss distribution approach and GARCH model, Communications for Statistical Applications and Methods, 2023, Vol. 30, No. 1, 75–94. By Sanghee Kim and Seongjoo Song. https://doi.org/10.29220/CSAM.2023.30.1.075
- On the long run volatility of stocks: time-varying predictive systems, Journal of the American Statistical Association, 2018, 113, 1050-1069. By Carlos Carvalho, Hedibert Lopes & Robert McCulloch.
- Bayesian prediction of risk measurements using copulas, in Bocker, K. (Ed.) Rethinking Risk Measurement and Reporting: Uncertainty, Bayesian Analysis and Expert Judgement, 2010, 553-578. By Ausin and Lopes. https://hedibert.org/wp-content/uploads/2013/12/ausin-lopes-2010.pdf
- Bayesian generalizations of the integer-valued autoregressive model, Journal of Applied Statistics. By Graziadei, Lopes and Marques (2020)
- Simulation-based sequential analysis of Markov switching stochastic volatility models, Computational Statistics and Data Analysis, 51 (9), 4526-4542. By Carvalho and Lopes (2006)
- Time Varying Structural Vector Autoregressions and Monetary Policy, The Review of Economic Studies, Vol. 72, No. 3, 821-852. By Primiceri (2005)
- Sparse Bayesian vector auto-regressions in huge dimensions, Journal of Forecasting, 30(7), 1142-1165. By Kastner and Huber (2020)

TEACHING MATERIAL

PART I: Basic univariate time series

1. Autoregressive (AR) models and moving average (MA) models (HTML output)
   - R code: Brief introduction to time series in R
   - R code: AR(1), random walk and AR(p) models
   - R code: ARMA & ARIMA models
2. Unit-root nonstationarity and long-memory processes (HTML output)
3. Seasonal models
   - SARIMA in R – Brazilian industrial production
   - R code for airline data – ARIMA(0,1,1)(0,1,1)[12] (R markdown html output)

PART II: Basic Bayes

1. Bayesian ingredients
   - *Gaussian vs Cauchy model & Gaussian prior*
   - *Gaussian linear regression (Koop and Tobias dataset)*
   - *Bayesian AR(1) with conjugate prior*
2. Bayesian computation

   - Monte Carlo (MC) methods
     - *Bayesian AR(1)*
     - *Bayesian AR(1) with Normal and t priors*
     - *Bayesian AR(2) with Normal and t priors*
     - *Bayesian AR(2) with Normal and t models (HTML)*
     - *Bayesian regression with autocorrelated errors*
     - *SIR, scale mixture of normals and raoblackwellization*
     - *Sampling from the log-chi-square distribution – SIR*
   - Markov chain Monte Carlo (MCMC) methods
     - *Bivariate normal – Gibbs sampler*
     - *Bayesian AR(p) – conjugate analysis vs Gibbs sampler*
     - *Random walk Metropolis: two toy examples*
     - *Comparing MCMC strategies – Gibbs, MH, block/single*
     - *Revisiting regression with autocorrelated errors: SIR vs Gibbs*
     - *Threshold AR (TAR) model: Gibbs and Metropolis steps*
   - MC and MCMC: Key References

PART III: Garch-type, dynamic linear and stochastic volatility models

1. Glossary of ARCH models
   - EGARCH, GARCH-M, TGARCH
   - Bayesian GARCH
2. Dynamic models
   - Dynamic linear regression – Rmarkdown
   - A few review papers:

     - Migon, Gamerman, Lopes and Ferreira (2005)
     - Schmidt and Lopes (2019)
     - Migon, Alves, Menezes and Pinheiro (2023)
   - Example 1: Local level model: fixed variances
   - Example 2: Simple dynamic regression: fixed variances
   - Example 3: Simple dynamic regression: learning variances
   - Example 4: BSTS package for state-space modeling of NO3 (Data)
   - Steve Scott's BSTS tutorial (my own shorter tutorial)
   - Hidden Markov Model: Variance Switching
   - Stochastic volatility models
   - Petrobras example: SV, SVt, SVl & SVtl
3. Sequential Monte Carlo – pure filter
   - Local level DLM & nonlinear DM
   - Stochastic volatility: MCMC vs SMC
   - Stochastic volatility: Particle filter (pure filters) vs Brute force MCMC

PART IV: Multivariate time series

1. Vector autoregressive models (VAR) part one
   - VAR and BVAR in R – a couple of examples
   - Minnesota prior for the trivariate BVAR(2)
2. VAR part two: Large BVAR, FAVAR, TVP-BVAR & BFAVAR
3. Bayesian factor analysis (BFA)
   - Bayesian factor analysis in R: a simple illustration (additional routines)

- Factor models: an annotated bibliography (2003)
- Lopes (2014)
- Factor modeling of pollutant NO3 (Data)

4. Time-varying covariance modeling

   - Factor stochastic volatility models
   - Efficient Bayesian inference for multivariate FSV models (Kastner, Fruewirth-Schnatter & Lopes)
   - Factor stochastic volatility with time varying loadings and Markov switching regimes (Lopes & Carvalho)
   - Cholesky realized SV models (Shirota, Omori, Lopes & Piao)
   - Bayesian inference for stochastic volatility modeling (Lopes & Polson)
   - A Review of Stochastic Volatility: univariate and multivariate models (Platanioti, McCoy & Stephens)
   - An bivariate example

Bonus topic: Time series meet machine learning

- Deep Learning Models For Inflation Forecasting (Theoharidis, Guillen and Lopes)
- Forecasting Inflation in a Data-Rich Environment: The Benefits of Machine Learning Methods (Medeiros, Vasconcelos, Veiga and Zilberman)
- Real-time inflation forecasting with high-dimensional models (Garcia, Mederios and Vasconcelos)
- Adaptive models and heavy tails with an application to inflation forecasting (Monache and Petrella)
- Deep learning with long short-term memory networks for financial market predictions (Fischer and Krauss)
- A comparison of time series and machine learning models for inflation forecasting. Empirical evidence from the USA (Sahin and Subasi)
- Empirical Asset Pricing via Machine Learning (Gu, Kelly, Xiu)

Old homework assignments (spring 2022): *HW1* (*Solution*) + *HW2* + *HW3* (*Derivations* + *R code*) + HW4: Fit Gaussian and Student's t GARCH(1,1) to your favorite returns (Coke, Apple, Amazon, S&P, etc) using the R packages garchFit and bayesGARCH that I have used in class. Feel free to add other (non-Bayesian) GARCH-type fits based on the ARCH-glossary that we have discussed in class. Use data between January 2005 and December 2021, so you are including the 2007-2008 financial crisis, as well as the 2020-2021 COVID pandemic. Comment your findings.