Readings in Statistics and Econometrics 2015: Causality

Organizer: Hedibert Freitas Lopes

In this First Readings in Statistics and Econometrics we will study and discuss, through a series of well established papers, the broad topic of causality. **Annotated bibliography:** Links to textbooks and edited books, special issues, articles with discussion and web material: slides of lectures, discussion of causality, video lectures and more. **Only articles and book chapters**.

Outline of the lectures

1. September 29th – Hedibert Lopes – INSPER
   Haavelmo (1943) The statistical implications of a system of simultaneous equations. Econometrica, 11, 1-12. Slides of the lecture
2. October 6th – Hedibert Lopes – INSPER
   Rubin (1974) Estimating causal effects of treatments in randomized and nonrandomized studies. Journal of Educational Psychology, 56, 688-701. Slides of the lecture
3. October 13th – André Yoshizumi, IME/USP
   Holland (1986) Statistics and causal inference (with discussion). JASA, 81, 945-970. Slides of the lecture
4. October 20th – Paloma Uribe, IME/USP
   Pearl (1995) Causal diagrams for empirical research (with discussion). Biometrika, 82, 669-710. Slides of the lecture
5. November 3rd – Sergio Firpo, EESP/FGV
   Angrist, Imbens and Rubin (1996) Identication of causal effects using instrumental variables (with discussion). JASA, 91, 444-472. Slides of the lecture
6. November 10th – Julio Trecenti, IME/USP
   Dawid (2000) Causal inference without counterfactuals (with discussion). JASA, 95, 407-424. Slides of the lecture
7. November 24th – Manasses Nóbrega, UFABC
   Vansteelandt and Goetghebeur (2003) Causal inference with generalized structural mean models. JRSS-B, 65, 817-835.
8. December 1st – Hedibert Lopes – INSPER
   Heckman and Pinto (2015) Causal analysis after Haavelmo. Econometric Theory, 31,115-151. Slides of the lecture

Books & special issues + articles with discussion (bottom 5 itens)

1. Journal of Econometrics (1988), Volume 39, Issues 1-2
2. Spirtes, Glymour and Scheines (2001) Causation, Prediction, and Search (2nd edition)
3. Gelman and Meng (2004) Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives
4. Dawid (2007) Fundamentals of Statistical Causality
5. Morgan and Winship (2007) Counterfactuals and Causal Inference: Methods and Principles for Social Research (2nd ed)
6. Angrist and Pischke (2008) Mostly Harmless Econometrics: An Empiricist's Companion
7. Pearl (2009) Causality: Models, Reasoning and Inference (2nd Edition)
8. Schroeder (2010) Accounting and Causal Effects: Econometric Challenges
9. Berzuini, Dawid and Bernardinelli (2012) {\em Causality: Statistical Perspectives and Applications
10. Morgan (2013) Handbook of Causal Analysis for Social Research
11. Imbens and Rubin (2015) Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction
12. Hernan and Robins (2015) Causal Inference
13. Econometric Theory (2015), Volume 31, Issue 01
14. Holland (1986) Statistics and causal inference. JASA, 81, 945-970.
15. Pearl (1995) Causal diagrams for empirical research. Biometrika, 82, 669-710.
16. Angrist, Imbens and Rubin (1996) Identification of causal effects using IVs. JASA, 91, 444-472.
17. Dawid (2000) Causal inference without counterfactuals. JASA, 95, 407-424.
18. Heckman (2005) The scientific model of causality. Sociological Methodology, 35, 1-150.

From the web

Andrew Gelman's blog + Cosma Shalizi's page
The randomized experiment as gold standard?
Resolving disputes between J. Pearl and D. Rubin on causal inference
Philip Dawid's explication of Pearl's model, and two ways of thinking about nonrandom sampling
More on Pearl/Rubin, this time focusing on a couple of points
The Roy causal model?
Why ask why? Forward causal inference and reverse causal questions
Judea Pearl's home + Journal of Causal Inference
Athey and Imbens on Machine Learning
Imbens and Wooldrige: Whats New in Econometrics?
Chris Auld's Remarks on Chen and Pearl (2013) Regression and Causation
Friends don't let friends do IV…but…Friends do let friends do IV
If correlation doesn't imply causation, then what does?

Readings in Statistics and Econometrics 2016: Bayesian statistical learning

Organizers: Hedibert Freitas Lopes & Paulo C. Marques F.

Objective: In this Second Readings in Statistics and Econometrics we will study and discuss, through a series of well established papers, the broad topic of Statistical Learning with an emphasis on its natural Bayesian solutions. The 5 lectures and 8 seminars will take place on Fridays between 10am and 12pm from January 29th to April 8th 2016. Paulo and I will give lectures discussing traditional Statistical Learning techniques, alternated with seminars given by the participants on papers presenting Bayesian counterparts to the techniques discussed in the lectures.

Outline of the meetings (5 lectures and 8 seminars)

- Lecture 1 on k-nearest neighors (k-NN)
- Seminar 1: Holmes and Adams (2002,2003)
- Seminar 2: Cucala, Marin, Robert and Titterington (2009)
- Lecture 2 on LASSO regularization
- Seminar 3: Griffin and Brown (2010,2012,2014)
- Seminar 4: Polson, Scott and Windle (2014)
- Lecture 3 on Random Forests
- Seminar 5: Chipman, George and McCulloch, (2010)
- Lecture 4 on Supporting Vector Machines
- Seminar 6: Tipping (2001)
- Seminar 7: Polson and Scott (2011)
- Lecture 5 on k-means Clustering
- Seminar 8: Paulo's brief review of Dirichlet Processes
- Seminar 9: Kulis and Jordan (2012)

Books

- An Introduction to Statistical Learning (James, Witten, Hastie and Tibshrani)
- Applied Predictive Modeling (Kuhn and Johnson)
- Bayesian Reasoning and Machine Learning (Barber)
- The Elements of Statistical Learning (Hastie, Tibshrani and Friedman)
- Machine Learning: A Probabilistic Perspective (Murphy)
- Pattern Recognition and Machine Learning (Bishop)
- Pattern Classification (Duda, Hart and Stork)
- Probability and Measure (Billingsley)
- Probability and Measure Theory (Ash and Doleans-Dade)
- Optimal Statistical Decisions (DeGroot)
- Theory of Statistics (Schervish)
- Principles of Uncertainty (Kadane)

Papers

- Chipman, George and McCulloch (2010) BART: Bayesian Additive and Regression Trees. AOAS, 4, 266-298.
- Cucala et al. (2009) A Bayesian Reassessment of Nearest-Neighbor Classification. JASA, 104, 263-273.
- Griffin and Brown (2010) Inference with normal-gamma prior distributions in regression problems. BA, 5, 171-188.
- Griffin and Brown (2012) Structuring shrinkage: some correlated priors for regression. Biometrika, 99, 481-487.
- Griffin and Brown (2013) Some priors for sparse regression modelling. BA, 8, 691-702.
- Holmes and Adams (2002) A Probabilistic NN Method for Statistical Pattern Recognition. JRSS-B, 64, 295-306.
- Holmes and Adams (2003) Likelihood Inference in NN Classification Models. Biometrika, 90, 99-112.
- Kulis and Jordan (2012) Revisiting k-means: New Algorithms via Bayesian Nonparametrics. Proc. XXIX ICML.
- Polson and Scott (2011) Data Augmentation for Support Vector Machines. BA, 6, 1-24.
- Polson, Scott and Windle (2014) The Bayesian Bridge. JRSS-B, 76, 713-733.
- Tipping (2001) Sparse Bayesian learning and the Relevance Vector Machine. JMLR, 1, 211-244.
- Marques and Pereira (2013) Predictive Analysis of Microarray Data.

Business Statistics 41000-81/82 – Spring Quarter 2013

Professor: Hedibert Freitas Lopes
Teaching Assistant: Samir Warty
Course syllabus
Course notes: 2 per page + 3 per page
Old exams: Final exam – Spring 2011 (solution) - Midterm exam – Spring 2011 (solution)
Homework assignments: Homework I (solution), Homework II (solution) (hw2-solution.xls), Homework III (solution), Homework IV (solution), Homework V (solution) (usedcars.xls) (usedcars.txt) (R code)

Additional class material

Class 8: May 20th and 21st
Profit on income, birth rate, SS recipients, CV deaths, pop. age 65 and older (R code)
Salary on position, years of experience and gender (R code)
National Longitudinal Survey of Youth regression (R code)
House price regression + models + ranked models (R code)

Class 7: May 13th and 14th
House price regression (R code)
Boston house price versus crime rate (R code)

Class 5: April 29th and 39th
Midterm solution (graphical summaries)

Class 4: April 22nd and 23rd
Why NOT to trust excel with your life
GDP growth (R code)
PM10 emissions (R code)
Mortality rates under 5-years of age (R code)
Revisiting the house price data
DJIA: 19 components form January 1981 to December 2012 (R code)

Class 3: April 15th and 16th
Conditional probability
Portfolio allocation: nasdaq and djia
Repeating the Fama example with 100 components from the S&P500 (R code)
Six Brazilian companies (R code)
Portfolio allocation: NYSE 73 components and NASDAQ 42 components (R code)

Class 2: April 8th and 9th
Height of MBA male students
Class 1: April 1st and 2nd
Kurtosis – measuring tail-thickness or extremity

Data sets
returns.txt – monthly returns on a broad based portfolio of Canadian assets (class notes page 12)
volume.txt – daily volume in the cattle pit (class notes page 15)
mutualfunds.txt – returns on different mutual funds such as the equally weighted market and T-bills (class notes page 18/19)
beer-production-US.txt – number of beers male MBA students claim they drink without getting drunk (class notes page 20)
temperature.txt – average daily temperature in Rio, Durham and Chicago - 1/1/1995 and 12/11/2008 (class notes page 83)
highest-temperatures.txt – highest temperatures per state in the US (class notes page 89)
unemployment.txt – unemployment rates per state in the US in 2004 (class notes page 92)
stockreturns-countries.txt – EOE, DAX, CAC40, FTSE100, Hang Seng, Nikkei, Singapore All Shares and S&P500 (class notes page 96)
houseprice.txt – house characteristics: price, size, neighborhood, number of bedrooms and bathrooms, etc (class notes page 122)
US.xls – social indicators per state in the US
nasdaq-djia.txt – NASDAQ and DJIA daily returns for the period between January 4th 2000 to December 31st 2008
SP500-dailyreturns.txt – S&P500 daily returns for the period between January 5th 2009 to September 24th 2009
SP500-monthlyreturns.txt – S&P500 daily returns for the period between February 1950 to August 2009
dowjones-components.txt – Daily returns for the components of the DJIA for the period between02/02/1997-12-29-2006
DJIA-19components-jan1981-dec2012.txt
sp500-components.txt – Daily returns for the components of the S&P500
sp500-ge.xls – GE and S&P500 daily returns for the period between January 2nd 1962 and November 19th 2009
GDP2008.xls – GDP in billions of US dollars
heights-weights.xls – Height and weight of several male MBA students
online-investment-portfolios.txt – Value of investiments (in thousands of dollars) for a sample of clients in the 40- and 50- age group
amsterdam-frankfurt-paris-london-1997.xls – Equally weighted porfolios (Amsterdam, Frankfurt, Paris, London)
profit.txt - salary.txt - boston-houseprice.txt - logwages-yearseducation.txt - GDPgrowth.txt & GDPgrowth.xls – pm10-emission.txt & pm10-emission.xls - mortality-under5.txt & mortality-under5.xls - Brazil.txt - nyse73-nasdaq42.txt

ECONOMETRIA – Turma 4ECO (Economia)

Período Letivo: 2016/2
Professor: Hedibert Freitas Lopes – www.hedibert.org
Monitora: Paloma Vaissman Uribe – PalomaVU@insper.edu.br

Programa de Ensino

Conteudo das aulas

Apresentacao do curso
- wage.R + wage.txt + wage.csv
- violencia.R + violencia.csv (Mapa da Violencia 2015)

Regressao Linear Simples – Parte 1: Minimos Quadrados Ordinarios & R2
- VendedoresRH.xls
- Mais sobre minimos quadrados ordinarios
- Modelando salario via anos de experiencia, posicao e sexo (Codigo R) (Dataset)
- House prices: preco, tamanho, quarto, banheiros, etc (Codigo R)
- Mais sobre R2: explicando GPA (Codigo R)
- Gauss and the invention of least squares (by Stigler, 1981)
- The discovery of the method of least squares (by Plackett, 1972)

Regressao Linear Simples – Parte 2: formas funcionais
- Mais sobre formas funcionais
- Modelos log-log, nivel-log, log-nivel, nivel-nivel para dados HOUSE2 (Codigo R)
- Modelos log-log, nivel-log, log-nivel, nivel-nivel para dados TESTESCORE (Codigo R)

Regressao Linear Simples – Parte 3: Suposicoes, propriedades e teste-t
- Comportamento do estimador da inclinacao
- caliescom.txt + caliescom.R
- height x weight, nba-wnba players + nba.csv + wnba.csv + Codigo R
- Records dos 100 metros rasos + dados + Codigo R

Analise de residuos
- houseprices-regressaomultipla + Codigo R

Regressao linear multipla
- temco.txt: conjunto de dados utilizado nas notas de aula sobre regressao linear simples.
- Bank wages: Mais sobre R2 e R2 ajustado para 15 modelos (Codigo R) (Dataset)
- Data on monthly earnings, education, several demographic variables, and IQ scores for 935 men in 1980. (Dataset) (Codigo R)
- Data on 4,137 US college students.(Dataset) (Codigo R)
- Tutorial em R – Parte I (Datasets: salario.txt & salario.csv)
- Tutorial em R – Parte II :(Dataset: houseprices.txt)
- Precos de imoveis via dummies – houseprices.txt
- Precos de imoveis via dummies & interacoes – houseprices.txt – Codigo R
- Salarios de um banco americano – bankwages.txt – Codigo R
- Precos de sucos de laranja – orangejuice-chicagoarea.csv – Codigo R
- Precos de Toyota Corollas usados – toyotacorolla.csv – Codigo R
- Peso vs altura, idade, sexo – peso-altura-idade-sexo-criancas.txt – Codigo R
- Monthly earnings, education, IQ, etc for 935 men in 1980 – wage2-wooldridge.txt – Codigo R

Regressao linear multipla – Vies de omissao de variable

Regressao linear multipla – Teste F Parcial

Heteroscedasticidade
- Exercicio de simulacao
- Worked example – Codigo R

Endogeneidade: variaveis instrumentais (worked examples)
- Algumas ilustracoes

Endogeneidade: estimacao

Endogeneidade: tests
- Return to education (women) – Codigo R

Basic time series – Codigo R
- Algumas series temporais (ipi.csv – pbr.csv)

Listas de exercicios
- Lista 1 (Regressao linear simples): Wooldridge – 2.2, 2.3, 2.4, 2.5, 2.7, 2.9, 2.11
- Lista 2 (Regressao linear multipla): Wooldridge – 3.3, 3.4, 3.5, 3.7, 3.9, 4.2, 4.3, 4.6, 4.9, 4.11
- Lista 3 (Heteroscedasticidade): Wooldridge – 8.1, 8.2, 8.3, 8.4, 8.5 + refazer os exemplos 8.1 (pg 250-251), 8.2 (pg 252), 8.4 (pg 257) e 8.7 (pg 268-269)
- Lista 4 (Endogeneidade): Wooldridge – 15.1, 15.2, 15.3, 15.7, 15.8 e 15.10 + refazer os exemplos 5.1 (pg 476-477), 5.2 (pg 477-478), 5.3 (pg 480-481) e 5.4 (pg 484-486).
- Lista 5 (Series temporais): Wooldridge – Refazer os exemplos 10.1, 10.2, 10.3, 10.4, 10.7, 10.9, 11.3, 11.4, 11.5, 11.6 e 11.7 + problemas 11.1, 11.2, 11.3, 11.4 e 11.5
- **Atividade 2** - Dados por escola do ENEM2015 – Analise exploratoria dos dados – Codigo R

Econometria em R

- Tutorial de R: aula 1
- Tutorial de R: aula 2
- Tutorial de R: regressao
- Tutorial de R: R2
- Introducao ao uso do R (Paloma Uribe)
- Using R for Introductory Econometrics (Florian Heiss)
- Econometric and time series modeling using R (Cribari-Neto)
- Introduction to programmingEconometrics with R (Bruno Rodrigues)
- Econometrics in R: Past, Present, and Future (Achim Zeileis & Roger Koenker)
- CRAN Task View: Econometrics (Achim Zeileis)
- R-Econometrics – Learn R for applied economics in a comprehensive way

Econometria em outras linguagens/pacotes

- PYTHON: Introductory Econometrics – Jeffrey M. Wooldridge: Capítulos 2 ao 8 usando PYTHON
- Kevin Sheppard's Python for Econometrics
- STATA: Introductory Econometrics – Jeffrey M. Wooldridge: Capítulos 2 ao 18 usando STATA
- Statistical Analysis in R, MATLAB, SAS, STATA and SPSS

Mais conjuntos de dados

- VendedoresRH.xls
- salario.txt: Salário vs posição, anos de experiência e sexo
- retornos-2014.csv: Retornos de Ambev, Vale, Petrobras, JBS, Natura, Gafisa, Lojas Americanas & Ibovespa
- bankwages.txt: Salario vs salario inicial, educacao, sexo, minoria e categoria
- wage2-wooldridge.txt: Monthly earnings, education, IQ, etc for 935 men in 1980
- gpa2-wooldridge.txt: Data on 4,137 US college students
- houseprices.txt: House prices vs offers, sqft, brick, bedrooms, bathrooms and neighborhood
- orangejuice-chicagoarea.csv: Weekly sales of 64oz orange juice containers in the Chicago area
- toyotacorolla.csv: Sales prices and vehicle characteristics of 1436 used Toyota Corollas
- peso-altura-idade-sexo-criancas.txt: peso vs altura, idade e sexo
- gpa2.txt: same as gpa2-wooldridge.txt
- temco.txt + temcoprod.txt
- hprice1.txt: dados sobre 88 residências.
- dadosmunicipais.csv: dados de 5848 municípios brasileiros (analfabetismo, renda, desigualdade)
- caliescom.xls: Performance media de 420 escolas em um teste padronizado.
- ceosal2.xls: Data on 177 chief executive officers.
- florida2000.xls: Florida 2000 presidential vote as of 5pm ET Saturday, Nov. 11, 2000 (after recount).
- temcoprod.xls: Características de funcionários de uma firma.
- simulados_producao.xls: Modelagem da produção de firmas de um determinado setor.
- Wooldridge's datasets: wage1.csv + smoke.txt +card.csv + mroz.csv + bwght.csv

ECONOMETRIA AVANCADA 2015
Professor: Hedibert Freitas Lopes
Monitor: Paloma Vaissman Uribe
Objetivo: O objetivo do curso é apresentar os conceitos e métodos de análise multivariada de dados, aplicando-os a dados reais e interpretando os resultados de forma prática. No curso de análise multivariada são utilizados conceitos de estatística básica e inferência, com ênfase na resolução de problemas reais e interpretação dos resultados. Na maioria dos estudos, a complexidade dos fenômenos estudados faz com seja necessário coletar informações sobre um conjunto de variáveis. A análise multivariada permite o estudo simultâneo de um conjunto de variáveis, aproveitando a estrutura de correlação existente entre as mesmas. Nesta disciplina são apresentadas técnicas de análise de dados quantitativos e qualitativos, discutindo aplicações nas áreas de marketing, operações, recursos humanos e finanças.

Programa de Ensino

Introducao ao R by Paloma Uribe (Material apresentado na 1a monitoria)

Lista de exercicios: Primeira lista (Solucao) + Segunda lista (Codigo R) (Solucao) + Terceira lista (Codigo R) (Solucao) + Quarta lista (Codigo R) (Solucao) + Quinta lista (exercicio resolvido)

Trabalhos em grupo: Trabalho 1 + Trabalho 2 + Trabalho 3 + Trabalho 4

Prova intermediaria: Prova (solucao)

Prova final: Solucao

Notas de aula

- PARTE I: Apresentacao + Introducao
- PARTE II: Modelos AR, MA & ARMA
- PARTE III: Metodologia Box & Jenkins
- PARTE IV: Modelos lineares nao-estacionarios
- PARTE V: Previsao + Previsao de AR(1) e AR(1)
- PARTE VI: SARIMA + SARIMA(1,1,1)x(1,1,1)
- PARTE VII: Modelos lineares dinamicos
- PARTE VIII: Modelos ARCH e GARCH
- PARTE IX: Tendencia-estacionario ou diferenca-estacionario?
- PARTE X: Modelos SV-AR(1)
- PARTE XI: Modelos Autoregressivos Vetoriais (VAR)
- PARTE XII: Cointegracao, regressao espuria, VAR+ECM

Codigo R

- PARTE I: airline – indicepluviometrico – loadfactor – macro – petrobras – exercicios
- PARTE IV: Random walk with drift – Teste ADF – Nelson&Plosser – Nelson&Plosser paper
- PARTE V: forecasting-airline – forecasting-GDP
- PARTE VI: Local level model (stey-by-step) + dynamiclinearmodels.R
- PARTE VIII: Trend stationarity or not?
- PARTE IX: SV-AR(1) in R + Volatility Index (VIX) versus SV-AR(1)
- PARTE X: I Exemplo de VAR + II Exemplo de VAR

Textos complementares

- PARTE VI:
  - Petris & Petroni (2011) State space models in R
  - Tusell (2011) Kalman filtering in R
  - Journal of Statistical Software (2011) – Volume 41 – Statistical Software for State Space Methods
- PARTE VII: Glossary to ARCH (GARCH) by Tim Bollerslev
- PARTE VIII: A critique of the application of unit root tests (John Cochrane, 1991)

Conjuntos de dados

- airline.txt
- presidenteprudente.txt – ribeiraopreto.txt
- american.txt – delta.txt – united.txt
- macro.csv
- petrobras.csv
- nelsonplosser-data.txt
- UKdriversKSI.csv
- vix-sp500.csv
- sp500.csv

Alguns sites interessantes para o curso

- Pacote estatistico R
- Pagina do livro de Morettin & Toloi
- Pagina do livro de Shumway & Stoffer
- Pagina do livro de Zivot & Wang
- Pagina do livro de Tsay

ECONOMETRICS III 2021 (TIME SERIES)
Professor: Hedibert Freitas Lopes
Teaching assistant: Bruno do Prado Costa Levy
Objective: The main goal of the course is to make the student familiar with and able to implement univariate and multivariate time series models by using both frequentist and Bayesian approaches. All classroom examples and implementations as well as projects will be carried out by the open-source statistical software R.
Course description: 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.
Bibliography
Gamerman and Lopes (2006) MCMC: Stochastic Simulation for Bayesian Inference, 2nd Edition. Chapman & Hall/CRC.
Tsay (2010) Analysis of Financial Time Series, Third Edition. Wiley-Interscience, Probability and Statistics.
Tsay (2014) Multivariate Time Series Analysis with R and Financial Applications. Wiley.
Shumway and Stoffer (2011) Time Series Analysis and Its Applications with R Examples, Third Edition. Springer.
Take-home midterm exam: 9am of Tuesday, February 23th to 12pm of Thursday, February 25th. (data)
Homework assignments

1. HW1: Problems 1,2,3,8,19,20 and 21, chapter 1 of Shumway and Stoffer's book (4th edition) - HW1 by Alexandre + HW1 by Livia + HW1 by Victoria
2. HW2: Problem 2.15 (page 107) of Tsay (2010). However, download the up-to-date quarterly gross domestic implicit price deflator time series from the Federal Reserve Bank of St Louis. Fit the ARIMA models with data up to the 4th quarter of 2018 and use 2019.I to 2020.III (7 quarters) for forecasting comparisons - HW2 by Thaline
3. HW3
4. HW4: Fit Gaussian and Student's t GARCH(1,1) to Vale S.A. (VALE) using the R packages garchFit, bayesGARCH and RSTAN that I have provided when we studied Petrobras (PBR). Feel free to add other (non-Bayesian) GARCH-type fits based on the ARCH-glossary that we have discussed in class.
5. HW5: Collect meaningful time-series (suggestion: Apple & SP500 for US market or Vale & Ibovespa for the Brazilian market). Use the time series in a simple CAP-M model which allows for time-varying slope. Repeat it by allowing ONLY time-varying slope. Then, allow both time-varying intercept and slope. Compare the three models to the benchmark OLS fit. You can use whatever Bayesian R package (such as bsts) that produces posterior summaries of the latent variables (intercepts and slopes) as well as static parameters. Comment your findings. There are lots of papers out there, and I recommend a 16-year old one here: Jostova and Philipov (2005) Bayesian analysis of stochastic betas, *Journal of Financial and Quantitative Analysis*, 747-778.

Paper presentations

- Graziadei, Lopes and Marques (2020) Bayesian generalizations of the integer-valued autoregressive model, *Journal of Applied Statistics.*
- Silva, Lopes and Migon (2006) The extended generalized inverse Gaussian distribution for log-linear and stochastic volatility models, *Brazilian Journal of Probability and Statistics*, 67-91.
- Carvalho and Lopes (2006) Simulation-based sequential analysis of Markov switching stochastic volatility models, *Computational Statistics and Data Analysis,* 51 (9), 4526-4542.
- Warty, Lopes and Polson (2018) Sequential Bayesian learning for stochastic volatility with variance-gamma jumps in returns, *Applied Stochastic Models in Business and Industry, 2018, 34, 460-483.*
- Prado and Lopes (2013) Sequential parameter learning and filtering in structured autoregressive state-space models, *Statistics and Computing,* 23 (1), 43-57.
- Primiceri (2005) Time Varying Structural Vector Autoregressions and Monetary Policy, The Review of Economic Studies, Vol. 72, No. 3, 821-852.
- Carriero, Todd and Massimiliano (2019) Large Bayesian vector autoregressions with stochastic volatility and non-conjugate priors, *Journal of Econometrics*, 212(1), 137-154.
- Shirota, Omori, Piao and Lopes (2017) Cholesky realized stochastic volatility model, *Econometrics and Statistics*, 2017, 3, 34-59.
- Kastner, Fruehwirth-Schnatter and Lopes (2017) Efficient Bayesian inference for multivariate factor SV models, *Journal of Computational and Graphical Statistics*, 26, 905-917.
- Kastner and Huber (2020) Sparse Bayesian vector auto-regressions in huge dimensions, *Journal of Forecasting*, 30(7), 1142-1165.
- Lopes, McCulloch and Tsay (2020) Parsimony inducing priors for large scale state-space models, *Journal of Econometrics* (Revised & Resubmitted).
- Levy and Lopes (2021) Dynamic ordering learning in multivariate forecasting.

Examples developed in class

1. Brief introduction to time series in R
2. AR(1), random walk and AR(p) models
3. ARMA & ARIMA models
4. ARFIMA models
5. Bayesian AR(1)
6. Bayesian AR(1) with Normal and t priors
7. Bayesian AR(2) with Normal and t priors
8. Bayesian AR(2) with Normal and t models
9. Bayesian nonlinear regression – SIR and RW-MH
10. Bayesian AR(p) – conjugate analysis vs Gibbs sampler
11. Comparing MCMC strategies – Gibbs, MH, block/single
12. Nonlinear regression – comparing SIR and Gibbs+RWMH
13. Bimodal posterior: comparing random-walk MH and independent MH + R code
14. Linear Gaussian regression with Normal-Half-Cauchy prior – MCMC with Gibbs and RWMH steps + R code
15. Petrobras (PBR): ARCH(1,1) + GARCH(1,1)
16. Petrobras (PBR): garchFit – bayesGARCH – rstan (stan file)
17. Modeling S&P 500 realized volatility & log returns (stan code + graphs + data)
18. Modeling COVID-19 death: an exercise in state-space modeling
19. Hamilton's (2017) paper "Why you should never use the HP filter"
20. SV-AR(1) for PBR: MCMC, SMC/particle filter and sequential MCMC (data)
21. Univariate stochastic volatility, factor analysis, & factor stochastic volatility
22. Bayesian time-varying covariance: DCC and FSV models (R code)

TEACHING MATERIAL

PART I: Basic univariate time series

1. Autoregressive (AR) models and moving average (MA) models (HTML output)
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
2. Monte Carlo (MC) methods
3. Markov chain Monte Carlo (MCMC) methods
4. Using stan/rstan for approximate Bayesian inference via Hamiltonian MC (HMC) methods
5. MC and MCMC: Key References

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

1. ARCH/GARCH-type models
   - Glossary of ARCH models
   - EGARCH, GARCH-M, TGARCH
   - Bayesian GARCH
2. Dynamic linear models (DLMs)
   - GARCH(1,1) versus stochastic volatility AR(1): motivating dynamic modeling (R code)
   - Local level model: $O(n^2)$ updates versus $O(n)$ updates (the FFBS) (R code)
   - Normal dynamic linear regression: Kalman, FFBS/MCMC and sequential MCMC (Rcode)
   - Normal dynamic linear regression: block sampling (FFBS) vs component-wise sampling (Rcode)
   - Toy DLM + Another toy DLM + AR1 + noise DLM
3. Nonlinear dynamic model – MCMC sampling individual states conditional on all other states
4. Sequential Monte Carlo – pure filter
   - Bootstrap filter (BF)
   - BF and sequential importance sampling (SIS)
   - BF, auxiliary particle filter (APF), optimal particle filter (OPF)
5. Sequential Monte Carlo – parameter learning
   - SMC with parameter learning
6. Stochastic volatility models
   - MCMC for the SV-AR(1) model
   - BF for the SV-AR(1) model
7. Using R packages "stochvol" & "rstan" for SV with Gaussian or Student's t errors

PART IV: Multivariate time series

1. Vector autoregressive models
   - R code for VAR, Chapter 2 of Tsay MTS book + packages
2. Large BVAR, FAVAR, TVP-BVAR & BFAVAR
   - Koop ad Korobilis (2009) Bayesian MTS Methods for Empirical Macroeconomics.
3. Factor models (Standard factor analysis, Spatial dynamic factors, Factor stochastic volatility)
4. Time-varying covariance 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)

Additional reading material on Bayesian time series

1. Bayesian Statistics (a very brief introduction) (Ken Rice, April, 2014)
2. Lopes and Salazar (2006) Bayesian model uncertainty in smooth transition autoregressions, *Journal of Time Series Analysis,* 27, 99-117.
3. Huerta and Lopes (2000) Bayesian forecasting and inference in latent structure for the Brazilian industrial production index, *Brazilian Review of Econometrics*, 20, 1-26.
4. Kleibergen and Hoek (2000) Bayesian Analysis of ARMA Models. Tinbergen Institute Discussion Paper.
5. Marriott, Ravishanker, Gelfand and Pai (1995) Bayesian Analysis of ARMA Processes: Complete Sampling Based Inference under Exact Likelihoods. *Bayesian Statistics and Econometrics: Essays in honor of Arnold Zellner*. Berry, Chaloner and Geweke, eds., John Wiley & sons, 241-254.

R stuff

Radford Neal's 13 lectures about R

McLeod, Yu and Mahdi's (2012) Time Series Analysis with R

MATERIAL FROM PREVIOUS YEARS (2018-2020)

Homework assignments and take-home exams

- Take-home midterm exames: 2020 + 2019
- Midterm exam 2017: solution
- 2020: HW1 + HW2 + HW3 (R code) + HW4 (R code)
- 2019: HW1: Simple MA model + Exercises 1.1 to 1.5 and 2.1 to 2.4 of Tsay (2010) - HW2 (dataset) - HW3: Problems 2.4, 2.5 and 2.6 of Tsay (2014).
- 2018: HW2: Exercises 3.1 and 3.2 of Hamilton (1994) and 2.7, 2.8 and 2.9 of Tsay (2010) - HW3
- 2017: HW1 (Solution to 2b and 2c + Additional MC exercise + Solution to 2d) - HW2 (dataset)

Paper presentations

- Del Negro and Schorfheide (2004) Priors from General Equilibrium Models for VARS. *IER,* 45, 643-673.
- Banbura, Giannone and Reichlin (2010) Large BVARs, *JAE*, 25(1), 71-92.
- Koop and Korobilis (2013) Large TVP VARs. *JoE*, 177, 185-198.
- Giannone, Lenza, Primiceri (2015) Prior selection for VARs. *The RES*, 97,436-451.
- Carriero, Clark, Marcellino (2015) BVARs: Specification choices and forecast accuracy. *JAE*, 30, 46-73.
- Chan and Eisenstat (2018) Bayesian model comparison for TVP VARs with SV. *JAE*, 33, 509-532.
- Carriero, Clark and Marcellino (2019) Large BVARs with SV and flexible priors. *JoE*, 212, 137-154.
- Kastner and Huber (2020) Sparse BVARs in huge dimensions, *JoF*, 30(7), 1142-1165.
- Korobilis and Pettenuzzo (2020) Adaptive hierarchical priors for HD-VARs. *JoE, 212(1), 241-271.*
- Koop, Korobilis and Pettenuzzo (2019) Bayesian Compressed VARs. *JoE*, 210, 135-154.

Examples developed in class

- 2020: ACF of white noise and random walk processes
- 2020: AR(3) simulation exercise(R markdown code)
- 2020: AR(1) models: predictive analysis (R markdown code)
- 2020: AR(3) models: Gibbs sampler (html) (Rmarkdown code)
- 2020: Our first Metropolis-Hastings algorithm
- 2020: Bayesian regression with the normal-gamma prior

- 2019: ACF of white noise and random walk processes
- 2019: AR(3) simulation exercise(R markdown code)
- 2019: Gaussian and non-Gaussian GARCH models + Rmarkdown + Petrobras data
- 2019: Our first state-space model: AR(1) plus noise model
- 2019: Linear regression with AR(1) errors (graphs)
- 2019: AR(1) plus noise model: FFBS
- 2019: AR(1) plus noise model: block-move vs single-move
- 2019: My first particle filter
- 2019: SV-AR(1): MCMC & SMC + (R code)
- 2019: SV & FSV + (R code) + (dados)
- 2019: DCC-GARCH & FSV + (R code)

- 2018: ACF of white noise and random walk processes
- 2018: AR(3) simulation exercise(R markdown code)
- 2018: Sampling distribution of the Dickey-Fuller ratio
- 2018: SARIMA for unemployment rate in Sao Paulo (R code)
- 2018: Sequential Bayesian learning
- 2018: Monte Carlo integration/simulation
- 2018: Gaussian AR(2) model with conditionally conjugate priors: Gibbs Sampler
- 2018: Bayesian linear regression
- 2018: Binomial model and mixture of betas prior: comparing SIR and Metropolis-Hastings schemes
- 2018: Bayesian CAPM
- 2018: Gaussian and non-Gaussian GARCH models + Rmarkdown + Petrobras
- 2018: Modeling time-varying variances via stochastic volatility (SV) models
- 2018: Hidden Markov model: forward filtering, backward sampling (Rmd code)
- 2018: VAR homework

- 2017: R code for the AR(2) example worked in class
- 2017: R for Shumway and Stoffer's chapter 1
- 2017: More R code for the AR(1) and AR(2) processes (Slides)
- 2017: R markdown script (run via Rstudio) (PDF output or HTML output)
- 2017: Monte Carlo exercise: studying the sampling behavior of the t test under unit root
- 2017: Bayesian inference for the Gaussian AR(2) model (R code)
- 2017: Computing pi via rejection sampling: our first MC sampling scheme
- 2017: MC integration for a simple normal-normal example
- 2017: Gibbs sampler for AR(1) model with a changing point (changing in the intercept)
- 2017: Brazilian monthly production of cement (January 2002 to February 2017)
- 2017: AR(1) plus noise + Figure 1 + Figure 2.
- 2017: AR(1) plus noise – Kalman filter and smoother + Figures.
- 2017: AR(1) plus noise – Bayesian inference via MCMC/FFBS + Figures.
- 2017: AR(1) plus noise – Modeling Alcoa realized volatilities via 1st order DLM + Data.
- 2017: AR(1) plus noise – Comparing block move (FFBS) with single move MCMC schemes
- 2017: Linear regression with Markov switching intercept – R code + Figures

Advanced Bayesian Econometrics 2025

Professor: Hedibert Freitas Lopes – www.hedibert.org
Objective: The end of the course goal is to allow the student to critically decide between a Bayesian, a frequentist or Bayesian-frequentist compromise when facing real world problems in the fields of micro- and macro-econometrics and finance, as well as in quantitative marketing, strategy and business administration. With this end in mind, we will visit well known Bayesian issues, such as prior specification and model comparison and model averaging, but also study regularization via Bayesian LASSO, Spike-and-Slab and related schemes, "small n, large p" issues, Bayesian statistical learning via additive regression trees, random forests, large-scale VAR and (dynamic) factor models.
Course description: Basic ingredients: prior, posterior, and predictive distributions, sequential Bayes, conjugate analysis, exchangeability, principles of data reduction and decision theory. Model criticism: Bayes factor, computing marginal likelihoods, Savage-Dickey ratio, reversible jump MCMC, Bayesian model averaging and deviance information criterion. Modern computation via (Markov chain) Monte Carlo methods: Monte Carlo integration, sampling-importance resampling, Gibbs sampler, Metropolis-Hastings algorithms. Mixture models, Hierarchical models, Bayesian regularization, Instrumental variables modeling, Large-scale (sparse) factor modeling, Bayesian additive regression trees (BART) and related topics, Dynamic models, Sequential Monte Carlo algorithms, Bayesian methods in microeconometrics, macroeconometrics, marketing and finance.
Part I Bayesian ingredients: i) Inference: likelihood, prior, predictive and posterior distributions; ii) Model criticism: Marginal likelihoods, Bayes factor, model averaging and decision theory; and iii) Computation: An introduction (Markov chain and sequencial) Monte Carlo methods.
Part II Multivariate models: i) Large-scale vector autoregressive models; ii) Factor models and other dimension reduction models; and iii) Time-varying high-dimensional covariance models.
Part III Modern Bayesian statistical learning: i) Mixture models and the Dirichlet process: handling non-Gaussian models; ii) Regularization: sparsity via shrinkage and variable selection; iii) Large vector-autoregressive and factor models: combining sparsity and parsimony; iv) Classification and support vector machines; v) Regression trees and random forests; and vi) Latent Dirichlet allocation: Text as data, text mining.

Paper presentations: i) *GP-VAR and Macroeconomic Uncertainty; ii) How Polarized are Citizens? Measuring Ideology from the Ground-Up; iii) Minnesota BART; iv) Text as Data; and v) What events matter for exchange rate volatility?*

Homework assignments
HW1: Repeat the AR(1) problem (Example 2 from Class 1), but this time with w(t) iid Student's t with nu=4 degrees of freedom. a) Plot both prior and posterior in the same figure. b) Which model is better, as far as Bayes Factor is concerned? c) Plot p(y(n+1)|y(1),…,y(n)) for w(t) ~ normal. d) Plot p(y(n+1)|y(1),…,y(n)) for w(t) ~ Student's t.
HW2: In my notes about the Monte Carlo (MC) methods, we illustrate the implementation of SIR where the target distribution is a three-component bivariate mixture of normals (page 26). Let us compare: a) Proposal A: bivariate normal proposal density presented in the notes (page 29); b) Proposal B: bivariate Student's t with the same location, 4 degrees of freedom and scale that replaces the multiplier 9 in the covariance matrix of Proposal A with the multiplier 4.5; c) Bonus: make the multiplier equal to 1 and play around with the number of degrees of freedom, say 1, 2, 3, 5, 10; d) Comment your findings.
HW4: Revisit the "Bayesian hierarchical linear regression (Class 4 – Example 6 below), by assuming now making beta[1]=beta[2]=…=beta[I]=beta, where the prior for beta is now Gaussian with mean 0.5 and variance 1.0. Repeat the change, but now let alpha[1]=…alpha[I]=alpha, where the prior for alpha is Gaussian with mean -4.0 and variance 25.0. Compare the models. In particular, compare the posterior distribution of the error variance, sigma^2 for the different hierarchical models.
HW3 + **HW5** + **HW6**

Material developed in class

- Example 1: iid Bernoulli trials & two alternative priors for proportion parameter
- Example 2: AR(1) model with normal errors (homework: Student's t errors)
- Example 3: Bivariate Student's t – learning correlation and degrees of freedom
- Example 4: Data augmentation/Gibbs sampler – Linkage example
- Example 5: Data augmentation/Gibbs sampler – Mean of Student's t data
- Example 6: Bayesian hierarchical linear regression – Gibbs Sampler
- Example 7: Bayesian hierarchical Beta-Binomial regression
- Example 8: Zero-inflated Poisson data
- HMC & STAN – Nonlinear regression illustration (R script + STAN script)
- HMC & STAN – AR(1) model with Student's t errors
- HMC & STAN – GARCH(1,1) model with Student's t errors
- HMC & STAN – SV-AR(1) model with Gaussian or Student's t errors
- Factor analysis (data)

LECTURE NOTES

PART I: Bayesian ingredients

- Basic Bayes
- Exchangeability
- Principles of data reduction
- More on estimators
- Decision theory (Nuisance parameters + travel insurance example)
- Introdução à Teoria da Decisão – by Victor Fossaluza (IME-USP)
- James-Stein estimator (from C.P.Robert's *The Bayesian Choice, 2nd edition*)
- Bayesian model criticism (pages 1-6 & 32-34)

Additional reading material:

- Gamerman and Lopes (2006) - Chapter 2 - Compact, but easy to read.
- Migon, Gamerman and Louzada (2014) - Chapters 2 to 4 - Classical and Bayesian inference.
- Gelman et al. (2013) - Chapters 1 and 2 - Application-oriented.
- Berger (1985) - Chapter 4 (Sections 4.1-4.4) - More technical.
- Parmigiani and Inoue (2009) *Decision Theory: Principles and Approaches* (Table of contentes)
- van de Schoot *et al.* Bayesian statistics and modelling. *Nat Rev Methods Primers*, 1 (2021).
- Discussion about p-values

PART II: Bayesian Computation

- Monte Carlo (MC) methods
- Markov chain: a brief review
- Markov chain Monte Carlo (MCMC) algorithms
- MC and MCMC: Key References
- More on Bayesian model criticism
- Hamiltonian Monte Carlo: A toy example
- Stan/rstan for posterior inference: Hamiltonian MC (HMC) methods
- Banana shaped bivariate target: MH vs HMC
- Bayesian hierarchical modeling – the Beta-Binomial case

PART III: Bayesian Learning

1. Modeling with mixtures of distributions
   - Finite mixture of distributions
   - Univariate mixture of normals: MCMC and EM algorithms
   - Multivariate mixture of distributions
   - AR(1) model with Markov Switching intercept
   - Linear regression with mixture of normal errors
   - How Many Data Clusters Are in the Galaxy Data Set? + The telescope sampling

2. Fundamentos de Aprendizagem Estatística + R code + MC exercise

3. Multiple linear regression: selection, shrinkage, sparsity
   - Motorcycle example
   - Slides from the 2015 School of Time Series and Econometrics tutorial
   - Hahn, He and Lopes (2018) Gaussian linear regression with arbitrary sparsity + slides of a talk
   - R package bayeslm
   - Fava and Lopes (2021) The illusion of the illusion of sparsity + slides of a talk + UFPE webinar
   - van Erp et al. (2019) Shrinkage priors for Bayesian penalized regression, JMP, 89, 31-50.
   - Michael Betancourt's Bayes Sparse Regression (stan/rstan example)

4. Classification: logistic regression and discriminant analysis
   - Sparse logistic regression for the spam/ham dataset (data)
   - Marketing campaigns of a Portuguese banking institution (data)
   - Sparse logistic regression: comparison of regularization and Bayesian implementations
   - Gelman et al. (2008) A weakly informative default prior distribution for logistic and other regression models, *AOAS*, 2(4), 1360-1383.
   - Polson et al. (2013) Bayesian Inference for logistic models using Pólya-Gamma latent variables, *JASA*, 108, 1339-1349.

5. Multivariate models and dimension reduction

   - Bayesian factor analysis (BFA)
   - BFA in R: a simple illustration (additional routines)
   - Factor models: an annotated bibliography (Lopes, 2003) + review chapter (Lopes, 2014)

- Principal components analysis (PCA), PCA-based and FA-based regressions
- Probabilistic PCA + Rcode + data

6. Classification and regression trees (CART)
   - Machine Learning course by Paulo Orenstein from IMPA.
   - Chapter 12 and Chapter 13 are about *Tree-based methods*.
   - Chapter 15 and Chapter 16 are about *Deep learning*.

7. Bayesian CART

8. Bootstrap aggregating (bagging)
   - Bootstrap illustration
   - CART step-by-step for the Boston housing data
   - CART for the motorcycle data

9. Bayesian additive regression trees (BART)
   - Example 1: ICU data: CART, BART and random forest (R code)
   - Example 2: Stock and Watson's (2002) macro data (data)
   - More examples: Four BART applications & 2 reviews + cute CART trees and 3D plots
   - More recent references

10. Latent Dirichlet Allocation (LDA)
    - Twitter + BBC + Dickens, Wells, Verne or Austen? + The cat in the hat by Dr. Seuss

11. Neural Networks

Complementary material to PART III
- Boosting (weak/stronger learners)
- Random forests
- Bayesian instrumental variables
- General linear and hierarchical models
- Limited dependent variable models
- Spatial models
- P.Richard Hahn's top 25 books on Statistics, Causal Inference, Statistical Computing, Machine Learning and Data Science

Bibliography: Bayesian econometrics
1.Zellner (1971) An Introduction to Bayesian Inference in Econometrics
2.Goel and Iyngar (1992) Bayesian Analysis in Statistics and Econometrics
3.West and Harrison (1997) Bayesian Forecasting and Dynamic Models (2nd edition)
4.Dorfman (1997) Bayesian Economics Through Numerical Methods
5.Bauwens, Lubrano and Richard (2000) Bayesian Inference in Dynamic Econometric Models
6.Koop (2003) Bayesian Econometrics
7.Geweke (2005) Contemporary Bayesian Econometrics and Statistics
8.Lancaster (2004) Introduction to Modern Bayesian Econometrics
9.Rossi, Allenby and McCulloch (2005) Bayesian Statistics and Marketing
10.Prado and West (2010) Time Series: Modeling, Computation and Inference
11.Geweke, Koop and Van Dijk (2011) The Oxford Handbook of Bayesian Econometrics
12.Greenberg (2013) Introduction to Bayesian Econometrics
13.Herbst and Schorfheide (2015) Bayesian Estimation of DSGE Models
14.Chan, Koop, Poirier and Tobias (2019) Bayesian Econometric Methods (2nd edition)
15.Broemeling (2019) Bayesian Analysis of Time Series
16.Bernardi, Grassi and Ravazzolo (2020) Bayesian Econometrics

Bibliography: Bayesian statistics
1. Berger (1985) Statistical Decision Theory and Bayesian Analysis
2. Bernardo and Smith (2000) Bayesian Theory
3. Gelman and Hill (2006) Data Analysis Using Regression and Multilevel/Hierarchical Models
4. Robert (2007) The Bayesian Choice
5. Hoff (2009) A First Course in Bayesian Statistical Methods
6. Carlin and Louis (2009) Bayesian Methods for Data Analysis (3rd edition)
7. Gelman, Carlin, Stern, Dunson, Vehtari and Rubin (2016) Bayesian Data Analysis
8. Migon, Gamerman and Louzada (2015) Statistical Inference: An Integrated Approach (2nd edition)
9. Reich and Ghosh (2019) Bayesian Statistical Methods
10. Held and Sabanes-Bove (2020) Likelihood and Bayesian Inference

Bibliography: Bayesian computation

1.Gilks, Richardson and Spiegelhalter (1995) Markov Chain Monte Carlo in Practice
2.Doucet, de Freitas and Gordon (2001) Sequential Monte Carlo Methods in Practice
3.Robert and Casella (2004) Monte Carlo Statistical Methods (2nd edition)
4.Gamerman and Lopes (2006) MCMC: Stochastic Simulation for Bayesian Inference, Second Edition
5.Marin and Robert (2007) Bayesian Core: A Practical Approach to Computational Bayesian Statistics
6.Albert (2009) Bayesian Computation with R
7.Brooks, Gelman, Jones and Meng (2011) Handbook of Markov Chain Monte Carlo
8.Givens and Hoeting (2012) Computational Statistics (2nd edition)
9.Marin and Robert (2014) Bayesian Essentials with R (complete solution manual)
10.Turkman, Paulino and Mueller (2019) Computational Bayesian Statistics: An Introduction
11.McElreath (2020) Statistical Rethinking: A Bayesian course with Examples in R and STAN
12.Chopin and Papaspiliopoulos (2020) An Introduction to Sequential Monte Carlo

Bibliography: Bayesian statistical learning

1. Bishop (2006) Pattern Recognition and Machine Learning
2. Hastie, Tibshirani and Friedman (2008) The Elements of Statistical Learning, 2nd edition
3. Murphy (2012) Machine Learning: A Probabilistic Perspective
4. Barber (2012) Bayesian Reasoning and Machine Learning
5. James, Witten, Hastie and Tibshirani (2013) An Introduction to Statistical Learning
6. Hastie, Tibshirani and Wainwright (2015) Statistical Learning with Sparsity
7. Efron and Hastie (2016) Computer Age Statistical Inference: Algorithms, Evidence and Data Science
8. Fernandez and Marques (2018) Data Science, Marketing and Business
9. Izbicki & Santos (2020) Aprendizado de máquina: uma abordagem estatística

Bibliography: Monte Carlo integration, simulation & Markov chain Monte Carlo

1. Metropolis and Ulam (1949) The Monte Carlo method. JASA, 44, 335-341.
2. Metropolis, Rosenbluth, Rosenbluth, Teller and Teller (1953) Equation of state calculations by fast computing machines. Journal of Chemical Physics, 21, 2087-1092.
3. Hastings (1970) MC sampling methods using Markov chains and their applications. Biometrika, 57, 97-109.
4. Peskun (1973) Optimum Monte Carlo sampling using Markov chains. Biometrika, 60, 607-612.
5. Besag (1974) Spatial Interaction and the Statistical Analysis of Lattice Systems. JRSS-B, 36, 192-236.
6. Kirkpatrick, Gelatt and Vecchi (1983) Optimization by Simulated Annealing. Science, 220 (4598), 671-680.
7. Geman and Geman (1984) Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images. IEEE Trans. Pattern Analysis and Machine Intelligence, 6, 721-741.
8. Pearl (1987) Evidential reasoning using stochastic simulation of causal models. AI, 32, 245-257.
9. Tanner & Wong (1987) The Calculation of Posterior Distributions by Data Augmentation. JASA, 82, 528-540.
10. Geweke (1989) Bayesian Inference in Econometric Models Using MC Integration. Econometrica, 57, 1317-39.
11. Gelfand and Smith (1990) Sampling-Based Approaches to Calculating Marginal Densities. JASA, 85, 398-409.
12. Casella and George (1992) Explaining the Gibbs Sampler. The American Statistician, 46, 167-174.
13. Gilks and Wild (1992) Adaptive Rejection Sampling for Gibbs Sampling. Applied Statistics, 41, 337-348.
14. Smith&Gelfand (1992) Bayesian Statistics without Tears: A Sampling-Resampling Perspective.TAS,46,84-88.
15. Chib and Greenberg (1995) Understanding the Metropolis-Hastings algorithm. TAS, 49, 327-335.

Bayesian Learning 2025

Professor: Hedibert Freitas Lopes
Teaching assistant: Guilherme Piantino
Syllabus: The ultimate goal of this course is to enable graduates to critically decide between the classical or Bayesian approach, or a combination of both, when faced with real-world decision-making problems under uncertainty. Areas where these real-world problems arise, as examples discussed throughout the course, include microeconomics, macroeconomics, finance, quantitative marketing, among many others. With this objective in mind, we will study the basic ingredients of the Bayesian paradigm: formulation of the binomial model-prior, model comparison and combination, computational aspects, and Bayesian decision-making. In the second part of the course, the Bayesian approach to traditional linear regression and logistic regression models will be introduced, as well as their modern versions where priors are treated as regularization mechanisms and sparsity inducers. Sparsity will be present throughout the 2nd and 3rd parts of the course when dealing with highly dimensional and/or highly complex models. In the third and final part of the course, we will present several statistical models currently used for this purpose, such as mixture models, hierarchical models, factor models, and regression tree models, as well as models based on neural networks and models that use texts and documents as data (text modeling). All, it is worth mentioning, under the unified and coherent Bayesian approach. All calculations during the course will be performed using the R statistical package.

Homework assignments
HW1 + HW2 + HW3: Choose one of the three STAN examples we worked in class (AR(1), GARCH(1,1) or SV-AR(1)) and run assuming Gaussian errors. Then, compare the results of both models, i.e. the model with Student's t errors and the model with Gaussian errors. The idea of this exercise is for you to familiarize yourself with STAN/RSTAN for Bayesian modeling. **HW4:** Replicate the PCA/FA exercise we worked out in the class of June 2nd 2025. **HW5:** In 2021, I worked on an example of predictive modeling where the response is binary (Bernoulli). See if you can replicate the exercise and understand the comparison between the various models: GLM (logistic regression), Bayesian GLM, Ridge/Lasso/Elastic net logistic regressions, CART, Random forest and BART. Here is some of the output for the Intensive Care Unit (ICU) data (from R package "aplore") and here is my R code

Final project – paper presentation:
Lista de artigos científicos
Papers assigned to each student

Additional examples developed/discussed in class

Mixture of Gaussian prior with unknown weights
Weight vs height: outlier, Gaussian vs Student's t errors
Learning the degree of freedom
Binomial vs Negative Binomial
Nonlinear regression: SIR, MCMC and MC methods
HMC: A toy example introduction
Stan/rstan for HMC-based posterior inference
HMC via ChatGPT (supervised by me!)
HMC & STAN – Nonlinear regression illustration (R script + STAN script)
HMC & STAN – AR(1) model with Student's t errors
HMC & STAN – GARCH(1,1) model with Student's t errors
HMC & STAN – SV-AR(1) model with Gaussian or Student's t errors
- HMC for (Physics) Dummies (Vats, 2023)
- MCMC using Hamiltonian dynamics (Neal, 2012)
- The Metropolis-Hastings-Green algorithm (Geyer, 2003)
- Introduction to statistical computing and HMC (Michael Betancourt, 2018)
- Geometric foundations of HMC (Michael Betancourt, 2014)
- Riemann Manifold Langevin and HMC Methods (Girolami & Calderhead, 2011)
- HMC for Hierarchical Models (Betancourt & Girolami, 2013)
- The No-U-Turn Sampler: Adaptively Setting Path Lengths in HMC (Hoffman and Gelman, 2014)

AR(p) models: Bayesian updating with conjugate prior vs Gibbs sampler
Return on education: Gaussian linear model with conjugate prior
Gaussian linear regression model: Gibbs sampler for conditionally conjugate prior
Subset selection via BIC and shrinkage/sparsity via regularizing priors – Stock and Watson's (2002) macro data
Logistic regression: GLM vs Bayesian GLM (R packages: UPG & stan_glm) + Graphical summaries of the results
Two more dataset for logistic regression
Default of credit card clients (dataset)
Example of principal component analysis and factor analysis
Inflation forecasting (Graphical output) + (dataset)
Example of latent Dirichlet allocation in R
Example of neural net in R (chatGPT assisted)

Course notes (+ R code & references)

Bayesian ingredients

- The Monty Hall problem
- Flipping one of three coins three times and observing three heads (R code)
- Chapter 1 of “Bayes’ Rule: A tutorial Introduction to Bayesian Analysis (Slide)
- Tiago Mendonca’s shiny for the physicists example
- Phisycists A, B, C and D: Normal model and 4 priors
- Histórias da Matemática: Da Contagem nos Dedos à Inteligência Artificial (by Marcelo Viana, IMPA)
    - Provavelmente não somos bons em probabilidade
    - Paradoxos de probabilidade
    - O segredo para ganhar o jogo
    - O problema dos testes falsos positivos
    - O paradoxo de Simpson
    - Esperança para a estrela solitária

Bayesian computation

- Monte Carlo Integration – Excerpts from chapter 3 of Gamerman and Lopes (2006)
- Banana-shape posterior: Posterior inference via SIR
- Learning the number of degree of freedom of a Student’s t (Rmarkdown)
- Bayesian regression with the normal-gamma (NG) prior
- A bit of Monte Carlo simulation and integration
- Back to the physicists example
- Normal vs skew-normal distributions: an exercise in Bayesian learning
- The potential fallacy of using the prior as proposal in SIR algorithms
- Bayesian learning of correlation in bivariate normal data via SIR algorithm
- Smith and Gelfand (1992) Bayesian Statistics without Tears. TAS, 46(2), 84-88.
- Hamiltonian Monte Carlo: a brief introduction

Bayesian linear regression

- Boston housing data: ML and Bayesian inference
- Motorcycle example
- Regressing weight on height: SIR for Gaussian and Student’s t models
- Bayesian regularization
- iid Bernoulli or logit regression or probit regression? (Rmarkdown)
- Bayesian Poisson regression model versus i.i.d. Poisson model
- Another example of Poisson regression
- A few R packages for Bayesian inference in linear models
- Stan/rstan: Bayes Sparse Regression

Bayesian classification via logistic regression

- Sparse logistic regression for the spam/ham dataset (data)
- Marketing campaigns of a Portuguese banking institution (data)
- Sparse logistic regression: comparison of regularization and Bayesian implementations
- Gelman et al. (2008) A weakly informative default prior distribution for logistic and other regression models, *AOAS*, 2(4), 1360-1383.
- Polson et al. (2013) Bayesian Inference for logistic models using Pólya-Gamma latent variables, *JASA*, 108, 1339-1349.

Other important modeling structures

Factor models (Additional material)

- Indice de Desenvolvimento Humano
- US market (data)
- Bayesian factor models
- Reducao de ruido com PCA e FA

Time-varying variance/covariance

- Stochastic volatility
- Factor Stochastic Volatility(FSV)
- FSV x Dynamic Conditional Correlation (DCC)

Finite mixture of distributions

Machine Learning 1: Tree models

- Classification and regression trees (CART)
  - CART step-by-step for the Boston housing data
  - CART for the motorcycle data
  - ROC and AUC
- Bayesian CART
- Bootstrap aggregating (bagging)
  - Ilustracao do bootstrap
- Boosting (weak/stronger learners)
- Random forests
  - Predicao da covid-19 com dados publicos do Hospital Israelita Albert Einstein/SP
- Bayesian additive regression trees (BART) + (Rob's notes) + (a list of slides/examples/people/papers)

Machine Learning 2: Modeling text

- Latent Dirichlet Allocation (LDA)
- Short list of slides and papers
- Example 1 & 2: Twitter & BBC
- Example 3: Dickens, Wells, Verne or Austen?

Machine Learning 3: Neural nets

- Neural Networks
- short list of slides and papers

Additional supporting material

- Stan/rstan for posterior inference: Hamiltonian MC (HMC) methods – by Hedibert Lopes (February 2021)
- MC and MCMC: Key References – by Hedibert Lopes (February 2021)
- R packages for Bayesian linear regression – by Hedibert Lopes (February 2020)
- R packages for Bayesian Econometrics – by Hedibert Lopes (March 2014)
- CRAN Task View on Bayesian Inference (July 2023)
- Mathematics for Machine Learning – by Deisenroth, Faisal and Ong (2020)
- Conceitos e analises estatisticas com R e JASP – by Luis Anunciação (September 2021)
- Data Science, Marketing and Business by Pedro Fernandes & Paulo Marques (October 2019)
- Aprendizado de Máquina: Uma Abordagem Estatística (by Rafael Izbicki & Tiago Mendonça)
- Estatística e Ciência de Dados (by Pedro Morettin & Julio Singer)

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, SVI & 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.

ADVANCED BAYESIAN STATISTICAL LEARNING 2023 - ASU
Professor: Hedibert Freitas Lopes

Syllabus

Course description: The end of the course goal is to expose the student to modern Bayesian solutions to highly structured and stochastic real world problems. We will visit well known Bayesian issues, such as prior specification/sensitivity, model comparison/criticism and model averaging, as well as Bayesian computation via various Monte Carlo methods. We approach regularization in linear and log-linear models via Bayesian LASSO, Spike-and-Slab priors and related sparsity-inducing priors. We cover decoupling shrinkage and selection strategies in a fully Bayesian decision framework. Other topics covered are finite and infinite mixtures for Bayesian semi- and non-parametric modeling, large-scale (dynamic/spatial) factor models, Bayesian additive regression trees (BART), Bayesian text modeling and modeling large-scale time-varying covariance matrices. All classroom examples and implementations as well as projects will be carried out by the open-source statistical software R.

Useful textbooks:

- Gamerman and Lopes (2006) MCMC: Stochastic Simulation for Bayesian Inference, 2nd Edition.
- Gelman, Carlin, Stern, Dunson, Vehtari and Rubin (2020) Bayesian Data Analysis, 3rd Edition.
- Migon, Gamerman and Louzada (2015) Statistical Inference: An Integrated Approach, Second Edition.
- Hoff (2009) A First Course in Bayesian Statistical Methods. Springer.

Homework assignments: HW1 + HW2 + HW3 + HW4

List of papers for final presentation

- The illusion of the illusion of sparsity – Fava and Lopes (2021), Brazilian Journal of Probability and Statistics, 35(4), 699-720 https://arxiv.org/abs/2009.14296
- A weakly informative default prior distribution for logistic and other regression models – Gelman, Jakulin, Pittau and Zu (2008), Annals of Applied Statistics, 2(4), 1360-1383. https://doi.org/10.1214/08-AOAS191
- Do forecasts of bankruptcy cause bankruptcy? A machine learning sensitivity analysis – Papakostas, Hahn, Murray, Zhou and Gerakos (2023), Annals of Applied Statistics, 17(1), 711-739. https://doi.org/10.1214/22-AOAS1648
- Forecasting with many predictors using Bayesian additive regression trees – Pruser (2019), Journal of Forecasting, Volume38, Issue7, November 2019, Pages 621-631. https://doi.org/10.1002/for.2587.

TEACHING MATERIAL

Bayesian ingredients

1. Basic Bayes
   - R code: Bernoulli iid, logit regression or probit regression? (Rmarkdown)
   - R code: Computing coronavac efficacy with logit, probit and clog-log generalized linear models?
   - R code: Space Shuttle Challenger O-Ring – binary/glm binomial
   - Count data: Poisson model, Gamma prior vs Poisson model, Log-normal prior (R code)
2. Exchangeability
3. Principles of data reduction
   - Discussion about p-values – P-values not only violate conditionality principle, but it is commonly mistaken as "the probability that the null hypothesis is true". Recall that, Pr(H0 is true|data) is a well-defined Bayesian quantity, while the p-value is the probability of the data (or its more extreme versions) given that the null hypothesis is true: Pr(data|H0 is true); a totally different quantity!
4. Decision theory + More on estimators
   - For those keen to learn a bit more about Bayesian statistical decision theory beyond my meager lecture notes, I recommend a few places: 1) Statistical Decision Theory and Bayesian Analysis (2nd edition) – Berger (1985); 2) The Bayesian Choice (2nd edition) – Robert (2007); 3) Decision Theory: Principles and Approaches – Parmigiani & Inoue (2009); 4) Lecture notes on "Bayes Methods and Elementary Decision Theory" by Wellner (University of Washington); and Lecture notes on "Evaluating the performance of estimators" by Pati (Texas A&M University).
5. Bayesian model criticism
6. Additional reading material:
   - Chapter 2 of Gamerman and Lopes (2006) – Compact, but easy to read.
   - Chapters 2-4 of Migon, Gamerman and Louzada (2014) – Classical and Bayesian inference.
   - Chapter 1 and 2 of Gelman et al. (2013) – Application-oriented.
   - Chapter 4 (Sections 4.1-4.4) of Berger (1985) – More technical

Bayesian Computation

1. Monte Carlo (MC) Methods
   - *Monte Carlo Integration and MCI via Importance function*
   - *More on MCI*
   - *Bayesian multinomial model – MC integration & SIR*
   - *Gaussian vs Cauchy model & Gaussian prior*
   - *Bayesian binomial vs Poisson models – SIR (Analytical derivations)*
   - *Gaussian, Student's t and switching – MCI via Importance function for model comparison*
   - SIR, scale mixture of normals and raoblackwellization
2. Markov chain Monte Carlo (MCMC) algorithms
   - Markov chain: a brief review
   - *Random walk Metropolis: two toy examples*
   - *An example of linear regression with missing regressors*
   - *Linear regression with autocorrelated errors: SIR vs Gibbs*
   - *Nonlinear regression – random walk Metropolis*
   - *Hamiltonian Monte Carlo: A toy example*
   - *Stan/rstan for posterior inference: Hamiltonian MC (HMC) methods*
   - *A few more examples developed in class (Stan code)*
   - MC and MCMC: Key References

Bayesian Learning

1. Multiple linear regression: selection, shrinkage, sparsity
   - Motorcycle example
   - Slides from the 2015 School of Time Series and Econometrics tutorial
   - Hahn, He and Lopes (2018) Gaussian linear regression with arbitrary sparsity (slides of a talk)
   - Fava and Lopes (2021) The illusion of the illusion of sparsity (slides of a talk)
   - Michael Betancourt's Bayes Sparse Regression (stan/rstan example)
   - Example 1: Normal linear models: subset selection via BIC and shrinkage/sparsity via regularizing priors (data)
   - Example 2: Normal linear models: k-fold cross-validation (data + R code)
   - Example 3: More on linear models: In-sample vs out-of-sample MSE/MAE (data + R code)
   - Example 4: More on linear models: Orthogonal vs factor-based X
   - Example 5: More on linear models: Larger wage dataset
2. Classification: logistic regression and discriminant analysis
   - Sparse logistic regression for the spam/ham dataset (data)
   - Marketing campaigns of a Portuguese banking institution (data)
   - Sparse logistic regression: comparison of regularization and Bayesian implementations
   - Gelman, Jakulin, Pittau and Zu (2008) A weakly informative default prior distribution for logistic and other regression models, *AOAS*, 2(4), 1360-1383.
   - Polson, Scott and Windle (2013) Bayesian Inference for logistic models using Pólya-Gamma latent variables, *JASA*, 108, 1339-1349.
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. Principal components analysis (PCA), PCA-based and FA-based regressions
5. Finite mixture of distributions
6. Spatial models
7. Bayesian CART
   - CART step-by-step for the Boston housing data
   - CART for the motorcycle data
   - Bootstrap illustration
8. Random forests
9. Bayesian additive regression trees (BART)
   - Example 1: ICU data: CART, BART and random forest (R code)
   - Example 2: Stock and Watson's (2002) macro data (data)
   - More examples: Four BART applications & 2 reviews + cute CART trees and 3D plots
   - More recent references
10. Latent Dirichlet Allocation (LDA)
11. Neural Networks
    - Bayesian two layer neural network (R code + tutorial in brnn package)
    - More comparisons (R code)
    -

Old homework assignments (spring 2022): *HW1* (*Solution*) + *HW2* (*Solution*) + *HW3* (*Derivations* + *R code*) + *HW4* (*Solution*)

Pool of papers from final presentation (spring 2022)

Análise Multivariada 2015

Professor: Hedibert Freitas Lopes

Monitor: Leandro Augusto Ferreira

Programa de Ensino

Objetivo: O objetivo do curso é apresentar os conceitos e métodos de análise multivariada de dados, aplicando-os a dados reais e interpretando os resultados de forma prática. No curso de análise multivariada são utilizados conceitos de estatística básica e inferência, com ênfase na resolução de problemas reais e interpretação dos resultados. Na maioria dos estudos, a complexidade dos fenômenos estudados faz com seja necessário coletar informações sobre um conjunto de variáveis. A análise multivariada permite o estudo simultâneo de um conjunto de variáveis, aproveitando a estrutura de correlação existente entre as mesmas. Nesta disciplina são apresentadas técnicas de análise de dados quantitativos e qualitativos, discutindo aplicações nas áreas de marketing, operações, recursos humanos e finanças.

1. **Análise exploratória de dados multivariados**
   Codigo R: descritiva – vinho – ILE-2013-R – bovespa
2. **Inferência multivariada – MANOVA**
   Codigo R: manova – bebidas
3. **Análise de componentes principais**
   Codigo R: bebidas-princomp – mundo – USArrests
4. **Análise fatorial – parte 1**
   Análise fatorial – parte 2
   Codigo R: exchange rates – british cohort study – retornos bolsa valores SP
5. **Regressão logística + Análise discriminante**
   Codigo R: Trator-RL – Arthritis-RL – Trator-LDA
6. **Correlação canonica**
   Codigo R: performance – psychometrics – carmarks – sales
7. **Cluster analysis**
   Codigo R: ILE-2013-cluster – IDHML-IDHMR
8. **Correspondence analysis & multidimensional scaling**
   IDHM brasileiro: Documentacao + Siglas + Dados + Codigo R
   Mais codigo R: correspondenceanalysis + multidimensionalscaling
9. **Conjoint analysis**
   Mensuração da estrutura de preferência do consumidor (J.O.Siqueira, Tese de mestrado, FEA/USP)
10. **Structural equation modeling**

Conjuntos de dados

- descritiva.csv
- vinho.txt
- ILE-2013.csv
- bovespa.csv
- bebidas.csv
- mundo.txt
- exchangerate-monthly.txt
- BCS-males.txt
- Ret2012.csv
- Trator.txt
- arthritis.txt
- vendedores.csv
- carmars.txt