

The 2017 Beijing Workshop on Forecasting

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by

School of Statistics and Mathematics

Central University of Finance and Economics

Venue

[academic.a'](#); Room to be announced via Email
Central University of Finance and Economics
39 Sout/ College Road, Chaoyang District, Beijing, China

Date

Saturday, November 18, 2017, 8:00-10:00 AM

In ite! "peakers

[Rob Anderson](#), Finance/ University

[Zunni Qian](#), Peking University

Sei Song, [2D.com](#)

[Luis Urrutia](#), University

[@an\)ei "ang](#), University

[%eng \\$i](#), Central University of Finance and Economics

#egistration

As registration fee is charged for all participants, but participants should scan this QR code to register for the works/ops before November 17, 2017.



Contact \$s

If you have any questions, please contact the local organizer [%eng \\$i](#) (Email: eng.i@ecufe.edu.cn), office: F7-13, 107712 Beijing

Program

0' (00)12(00 *e+note ,ecture on Forecasting

S'ea(er" Ro3 .#ndman+ , onas/ Universit#



Rob J Hyndman is Professor of Statistics in the [Department of Econometrics and Business Statistics](#) at [Monash University](#). He is also Editor-in-Chief of the [International Journal of Forecasting](#) and a Director of the [International Institute of Forecasters](#). Rob is the author of over 150 research papers and 5 books in statistical science. In 2007, he received the Moran medal from the Australian Academy of Science for his contributions to statistical research, especially in the area of statistical forecasting. For over 30 years, Rob has maintained an active consulting practice, assisting hundreds of companies and organizations around the world. He has won awards for his research, teaching, consulting and graduate supervision.

Topic I(Forecast accurac+ an! e aluation

.o4 do 4e decide 4/ic/)orecasting met/od is t/e 3est)or our time seriesH &/ere /ave 3een severa' measures o))orecast accurac# proposed+ 4/ic/ 4i'' 3e discussed. Ie 4i'' a'so 'ook at /o4 t/ese can 3e used to se'ect a)orecasting mode')or a given time series.

Topic II(-uto&atic ti&e series forecasting(.T"/ - #I0 -/ "T, 0/TB-T"/ F- " "T.

, an# app'ications reCuire a 'arge num3er o) time series to 3e)orecast comp'ete'# automatica'##. %or e5amp'e+ manu)acturing companies o)ten reCuire 4eek'#)orecasts o) demand)or t/ousands o) products at do9ens o) 'ocations in order to p'an distri3ution and maintain suita3'e inventor# stocks. In t/ese circumstances+ it is not)easi3'e)or time series mode's to 3e deve'oped)or eac/ series 3# an e5perienced ana'#st. Instead+ an automatic)orecasting a'gorit/m is reCuired. I 4i'' descri3e some o) t/e 3est automatic)orecasting a'gorit/ms t/at are 4ide'# used in practice+ as 4e'' as a ne4 met/od t/at /as on'# 3een recent'# proposed. (' o) t/e a'gorit/ms are imp'emented in R.

Topic III(1ierarchical forecasting

&ime series can o)ten 3e natura'## disaggregated in a /ierarc/ica' or grouped structure. %or e5amp'e+ a manu)acturing compan# can disaggregate tota' demand)or t/eir products 3# countr# o) sa'e+ retai' out'et+ product t#pe+ package si9e+ and so on. (s a resu't+ t/ere can 3e mi''ions o) individua' time series to)orecast at t/e most disaggregated 'eve'+ p'us additiona' series to)orecast at /ig'er 'eve's o) aggregation. (common constraint is t/at t/e disaggregated)orecasts need to add up to t/e)orecasts o) t/e aggregated data. &/is is kno4n as)orecast Jco/erenceK. I /en 4e turn inco/erent)orecasts into co/erent)orecasts+ 4e ca'' it J)orecast reconcilia'ionK. I 4i'' s/o4 t/at t/e optima' reconcilia'ion met/od invo'ves)itting a 'inear regression mode' 4/ere t/e design matris /as one co'umn)or eac/ o) t/e series at t/e most disaggregated 'eve'. -ut 4it/ /uge num3ers o)

time series+ t/e mode' is impossi3'e to estimate using standard regression a'gorit/ms. I 4i'' s/o4 /o4 t/e /ts package)or R so'ves t/is pro3'em.

12(20)13(20 Demographic and Economic Forecasting

12(20)14(10 Bayesian Demographic Estimation and Forecasting

S'ea(er: Zunni ? /ang+ Peking Universit#

)bstract: &/ere is a natura')it 3et4een -a#esian statistics and demograp/ic estimation and)orecasting. -a#esian met/ods can cope 4it/ comp'e5 mode's and nois# data+ 4/ic/ are common in demograp/ic estimation and)orecasting. -a#esian met/ods a'so provide ric/ measures o) uncertaint#. In t/e ta'k+ 4e 4i'' descri3e a 'ong term pro>ect to deve'op met/ods and so)t4are)or -a#esian demograp/#. &/e pro>ect emp/asises disaggregated estimates and)orecasts. I e 4i'' give an overvie4 o) our)rame4ork+ and present some i''ustrative resu'ts.

14(10)14(30 5D " &art "uppl+ Chain Dri en b+ -I

S'ea(er: \$ei Song+ Senior , ac/ine \$earning *ngineer+ 2D.com

)bstract: In 2D+ (I tec/no'ogies /ave 3een app'ied in man# areas o) our 3usiness+)or instance S"U recommendation+ drones+ automatic 4are/ouses etc. In t/is ta'k+ I 4i'')ocus on anot/er important app'ication o) (I in 2D+ name'# supp'# c/ain management. I 4i'' s/o4 #ou /o4 4e 'everage (I tec/no'ogies to drive ever# process o) our smart supp'# c/ain+ 4/ic/ inc'udes demand)orecast+ automatic rep'enis/ment+ S"U a''ocation+ markdo4n etc.

14(30)13(20 Forecasting ti&e series 6ith co&ple7 seasonal patterns using singular spectru& analysis

S'ea(er: .ui -u+ -ei/ang Universit#

)bstract: &ime series)rom 3usiness and economics ma# /ave mu'tip'e seasona' components+ 4/ic/ ma# 3e di)icu't to identi)# 4/en mu'tip'e seasona' autoregressive integrated moving average ;(RI , (< mode's are 3ui't. &o so've t/is pro3'em+ 4e propose a speci)ication met/od)or mu'tip'e S(RI , (mode'+ ca'ed SS(S(RI , (procedure+ t/at dra4s on t/e advantages o) singu'ar spectrum ana'#sis ;SS(< and t/e -o5 2enkins standard procedure o) t/e seasona' (RI , (;S(RI , (< mode' to reduce t/e /uman in)'uence. &/is paper uti'i9es mont/'# passenger t/roug/put data o) t/e .ong "ong and San %rancisco airports to test t/e proposed SS(S(RI , (mode'ing met/od. I e compare t/e out o) samp'e)orecasting per)ormance o) mu'tip'e S(RI , (mode')o''o4ing SS(S(RI , (procedure and t/e standard -o5 2enkins procedure+ SS(recurrent)orecasting met/od+ /#3rid mode' o) SS(and S(RI , (and /#3rid mode' o) 4ave'et and S(RI , (. &/e empirica' resu'ts s/o4 t/at dou3'e seasona' (RI , (mode's identi)ied 3# our met/od 3etter)it t/e data and improve t/eir out o) samp'e)orecasting per)ormance.

13(30)17(20 Probabilistic Forecasting

13(30)18(20 Probabilistic hierarchical forecasting

S'ea(er: Ro3 .#ndman+ , onas/ Universit#

Abstract: Forecasting hierarchical time series has seen a great interest in recent years. However, the literature has mainly focused on obtaining point forecasts that are coherent across a hierarchy. Instead, I focus on the problem of producing probabilistic forecasts for hierarchical time series. First, we look at how to define coherence in a probabilistic setting. Then we look at some results for probabilistic coherence assuming Gaussian forecast densities. Finally, we relax the Gaussian assumption and propose a novel non-parametric approach to generate coherent forecasts. We simulate future sample paths of the hierarchy incorporating bootstrapped in-sample errors and reconciling these so that they become coherent. We evaluate both approaches via extensive Monte Carlo simulations.

18(20)17(00 Improving forecasting performance using copulae

Independent copula models

Speaker: Mengqi Central University of Finance and Economics

Abstract: Copulas provide an attractive approach for constructing multivariate distributions and their marginal distributions and different forms of dependence. The particular importance in many areas is the possibility of explicit forecasting of the tail dependence. Most of the available approaches are not able to estimate tail dependence and correlations via nuisance parameters but can neither be used for interpretation nor for forecasting. (In order to improve copula forecasting performance, we propose a general -asian approach for modeling and forecasting tail dependence and correlations as explicit functions of covariates. The proposed copula dependent copula model also allows for -asian variable selection among covariates from the marginal models as well as the copula density. The copulas we study include the Clayton copula, Clayton copula, Gumbel copula and Student's t copula. Posterior inference is carried out using an efficient MCMC simulation method. Our approach is applied to both simulated data and the S&P 500 and S&P 700 stock indices. The forecasting performance of the proposed approach is compared with other modeling strategies based on log predictive scores. Value at Risk evaluation is also performed for model comparisons.

17(00)17(20 Forecasting using time series feature spaces

Speaker: Anthony Wang, University of

Abstract: This paper investigates the diversity of the 3 dataset used in most forecasting research and shows how a time series dataset can be visualized as a point in a 40 dimensional space. According to the Area Under the Curve, there is no one time series forecasting method that always performs best. Given that the statistical features of time series have an impact on their forecasting accuracies, we aim to examine how these features influence forecasting method performances through simulations from mixture autoregressive processes. (Ridge models can help us to predict the performances of the forecasting methods on the 3 data and select the best forecasting method. Finally, we propose a new method for generating new time series with controllable characteristics that aim to enrich the diversity of the feature space. We provide potential more insights than the current space.