Bayesian Bi-directional Self-Exciting Threshold Autoregressive Models for Loss Reserving

Yuning Zhang[1], **Wilson Ye Chen[1]**, S.T. Boris Choy[1], Tak Kuen Siu[2]

[1]University of Sydney, [2]Macquarie University

ABSTRACT

This work introduces the BiSETAR model, a novel approach to loss reserving that incorporates threshold uncertainty within a coherent Bayesian framework. Stochastic models with time-evolving parameters are generally considered state-of-the-art in addressing challenges posed by sudden large claims and irregular claim behaviours, but they treat threshold parameters as hyperparameters and neglect the uncertainty associated with these thresholds. The key contribution of this work is the introduction of a Bayesian method that treats threshold parameters as model parameters, allowing for the direct quantification of their uncertainty through the posterior distribution. To implement this, an efficient MCMC sampling algorithm is developed to approximate the posterior distribution of the threshold parameters. By incorporating bi-directional dynamics and threshold uncertainty into the forecasting process, the model significantly enhances the robustness and accuracy of loss forecasts, providing a more coherent and reliable framework for loss reserving.

Keywords: Bayesian Modelling, Threshold Autoregressive Model, Loss Reserving, Run-off Triangle

Loss-based Bayesian Sequential Prediction of Value-at-Risk with a Long-Memory and Non-linear Realized Volatility Model

Rangika Peiris, Minh-Ngoc Tran, **Chao Wang**, Richard Gerlach*

Discipline of Business Analytics, The University of Sydney

ABSTRACT

A long-memory and non-linear realized volatility model class is proposed for direct Value-at-Risk (VaR) forecasting. This model, referred to as RNN-HAR, extends the heterogeneous autoregressive (HAR) model, a framework known for efficiently capturing long memory in realized measures, by integrating a Recurrent Neural Network (RNN) to handle the non-linear dynamics. Quantile loss-based generalized Bayesian inference with Sequential Monte Carlo is employed for model estimation and sequential prediction in RNN-HAR. The empirical analysis is conducted using daily closing prices and realized measures with around 12 years of data till 2022, covering 31 market indices. The proposed model's one-step-ahead VaR forecasting performance is compared against a basic HAR model and its extensions. The results demonstrate that the proposed RNN-HAR model consistently outperforms all other models considered in the study. The implementation code of the HAR-RNN model is publicly available on Github: https://github.com/chaowang-usyd/RNN-HAR.

Keywords: HAR model; Recurrent Neural Network; Quantile Score; Sequential Monte Carlo; Generalized Bayesian inference.

Estimating Heterogeneous Treatment Effects through Multilevel Modeling

Tu Duong Quach[1], **Nuttanan Wichitaksorn[1]**, Kiet Nguyen[2], and Joshua D. Hawley[3]

[1]*Department of Mathematical Sciences, Auckland University of Technology, New Zealand*

[2]*University of Economics Ho Chi Minh City, Vietnam*

[3]*John Glenn College of Public Affairs and Center for Human Resource Research, Ohio State University, USA*

ABSTRACT

We propose a novel design for event studies using multilevel/hierarchical modeling. We show that the average treatment effect on the treated can be recovered from the variance of the nested random intercepts, and the heterogeneous treatment effects can be decomposed into two components: homogeneous treatment effects and the difference in outcomes between treated units. To illustrate our methodology, we revisit two studies on minimum wage policy and hospitalization. We thereby point out the pitfalls of the pre-trend testing when comparing one or a nearby period and fail to capture the heterogeneity.

Keywords: Multilevel modeling, Hierarchical modeling, Difference-in-differences, Heterogeneous treatment effects

Predicting the Weekly Return Direction of the S&P 500 Index Using DNN for Time Series Classification

Sang-Hyeok Lee

Department of Big Data, Small Enterprise and Market Service

ABSTRACT

This study explores the short-horizon predictability of the S&P 500 index by reformulating return forecasting as a binary time-series classification problem. Using deep neural networks, we predict whether the average return of the upcoming week will exceed that of the current week. Among 48 candidate architectures, a multilayer perceptron (MLP) model achieved the highest test accuracy (71.62%), outperforming both convolutional alternatives and six classical machine learning models. Beyond statistical metrics, we assess the economic value of the model's predictions through four trading strategies: Buy & Hold, Buy & Sell, Accuracy-Weighted, and Precision-Weighted. The Buy & Sell strategy delivered a cumulative return of 9,151%, while the Precision-Weighted strategy achieved the highest Sharpe ratio (3.08) and lowest Value-at-Risk (VaR). These results demonstrate that directional signals derived from deep learning can yield economically meaningful and risk-adjusted excess returns in weekly equity forecasting. Our findings challenge the strong form of market efficiency by uncovering persistent short-term patterns in price dynamics. The results also underscore the value of incorporating model confidence—through accuracy and precision—into portfolio construction. This research contributes to the growing literature on deep learning in finance by offering a robust and interpretable framework for short-term prediction and strategy design.

Keywords: Deep Learning, Time Series Classification, S&P 500 Forecasting, Short-Term Predictability