LMU LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN INSTITUT FÜR STATISTIK

An interpretable machine learning workflow for statistical inference

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and online via Zoom (Link)
(Meeting-ID: 913-2473-4411; Password: StatsCol22)

We propose a generic workflow for the use of machine learning models to inform decision making and to communicate modelling results with stakeholders. It involves three steps: (1) a comparative model evaluation, (2) a feature importance analysis and (3) statistical inference based on Shapley value decompositions. We discuss the different steps of the workflow in detail and demonstrate each by forecasting changes in US unemployment one year ahead using the well-established FRED-MD dataset. We find that universal function approximators from the machine learning literature, including gradient boosting and artificial neural networks, outperform more conventional linear models. This better performance is associated with greater flexibility, allowing the machine learning models to account for time-varying and nonlinear relationships in the data generating process. The Shapley value decomposition identifies economically meaningful nonlinearities learned by the models. Shapley regressions for statistical inference on machine learning models enable us to assess and communicate variable importance akin to conventional econometric approaches. While we also explore high-dimensional models, our findings suggest that the best trade-off between interpretability and performance of the models is achieved when a small set of variables is selected by domain experts.

Biography:
Andreas received his PhD from City University of Hong Kong in 2014 working on international trade and financial networks. He then briefly moved to the economics department of the European Central Bank before arriving at the Bank of England's Advanced Analytics division in 2015. Here, Andreas mostly works on the development and use of machine and deep learning techniques in a policy context, such as model inference and interpretability, and more recently reinforcement learning in macroeconomics.