Dynamic modeling and Bayesian predictive synthesis

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Abstract

This dissertation discusses model and forecast comparison, calibration, and combination from a foundational perspective. For nearly five decades, the field of forecast combination has grown exponentially. Its practicality and effectiveness in important real world problems concerning forecasting, uncertainty, and decisions propels this. Ample research– theoretical and empirical– into new methods and justifications have been produced. However, its foundations– the philosophical/theoretical underpinnings upon which methods and strategies are built– have been unexplored in recent literature. Bayesian predictive synthesis (BPS) defines a coherent theoretical basis for combining multiple forecast densities, whether from models, individuals, or other sources, and generalizes existing forecast pooling and Bayesian model mixing methods. By understanding the underlying foundation that defines the combination of forecasts, multiple extensions are revealed, resulting in significant advances in the understanding and efficacy of the methods for decision making in multiple fields.

The extensions discussed in this dissertation are into the temporal domain. Many important decision problems involve time series, including policy decisions in macroeconomics and investment decisions in finance, where decisions are sequentially updated over time. Time series extensions of BPS are implicit dynamic latent factor models, allowing adaptation to time-varying biases, miscalibration, and dependencies among models or forecasters. Multiple studies using different data and different decision

problems are presented, demonstrating the effectiveness of dynamic BPS, in terms of forecast accuracy and improved decision making, and highlighting the unique insight it provides