Abstract

Recent advancements in time series forecasting have addressed several crucial challenges associated with heterogeneous data and hierarchical structures. This comprehensive thesis introduces two interconnected frameworks that enhance forecasting accuracy and adaptability. First, we present a novel approach utilizing the dynamic time warping similarity measure to build neighborhoods for heterogeneous time series. This method allows for a new way of model averaging, which improves forecasts and allows for theoretical justification and enhanced diagnostic capabilities. To better understand the effects of forecast reconciliation on temporally hierarchical structures, we bridge the gap between hierarchical forecast reconciliation and temporal aggregation. Our analysis examines their theoretical relationships with a particular focus on temporally aggregated ARIMA models. This theoretical analysis reveals that the optimal reconciliation method aligns with a bottom-up aggregation approach, a finding supported by extensive simulation studies and real-world applications. Second, we develop an innovative framework for hierarchical forecast updating that effectively addresses partially observed data within temporal hierarchies. This framework enables coherent forecast updates across the entire hierarchy by integrating real-time data through a two-step process: first, updating base models and then applying a pruning step before reconciliation. The framework's effectiveness is demonstrated through comprehensive simulation studies and two case studies in the energy sector, showing significant improvements over traditional base models. Together, these methodological advances provide a robust foundation for handling complex forecasting scenarios, particularly in domains requiring temporal aggregation, hierarchical structuring, and real-time updating capabilities. The proposed frameworks offer both theoretical insights and practical tools for improved forecasting accuracy and better decision-making.