

Graphical Dynamic Models & Scaling Multivariate Time Series Methodology

I discuss some of our recent R&D with dynamic statistical models for multivariate time series forecasting that represents a shift in modelling approaches in response to the coupled challenges of scalability and model complexity. Building “simple” and computationally tractable models of univariate time series is a starting point. [Decouple/Recouple](#) is an overlaid strategy for coherent Bayesian analysis: That is, “decouple” a high-dimensional system into the lowest-level components for simple/fast analysis; and then, “recouple”– on a sound theoretical basis– to rebuild the larger multivariate process for full/formal/coherent inferences and predictions.

These goals are addressed in simultaneous graphical dynamic linear models (SGDLMs). Bayesian dynamic dependency networks (DDNs– Zhao *et al* 2016) represent a subclass with so-called Cholesky volatility structure; sequential filtering and forecasting in the subclass combines fast analytic updates and direct simulation methods. In the general class of SGDLMs (Gruber and West 2016a,b), a synthesis of importance sampling and variational Bayes methods define a decouple/recouple strategy for sequential filtering and forecasting. Studies in financial time series forecasting and portfolio decisions highlight the utility of the models. The advances in Bayesian dynamic modelling– and in thinking about coherent and implementable strategies for scalability to higher-dimensions (i.e. to “big, dynamic data”)– are exemplified in this context.

Aspects of this talk represent recent joint work with: [Zoey Zhao](#) (2013 PhD, Duke University) at Citadel llc, Chicago; [Lutz Gruber](#) (2015 PhD, Technical University of Munich) at Quantco, Cologne; and [Meng Amy Xie](#) (2012 BS, Duke University) in the PhD program in Statistical Science at Duke. Some current interests lie in collaborations in macro-economic applications.

References

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- [2] L. F. Gruber and M. West. Bayesian forecasting and scalable multivariate volatility analysis using simultaneous graphical dynamic models. *Technical Report, Duke University* (submitted), 2016b. <https://arxiv.org/abs/1606.08291>
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