



Ken



Daniele

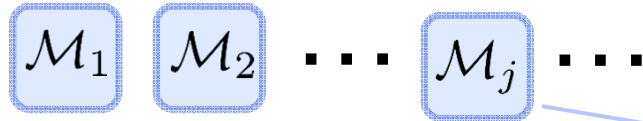


*Comments on*  
**Large-Scale Dynamic Predictive Regressions**  
by Daniele Bianchi & Kenichiro McAlinn

Mike West



Forecast future time  $t$  : Vector outcome  $\mathbf{y}_t$



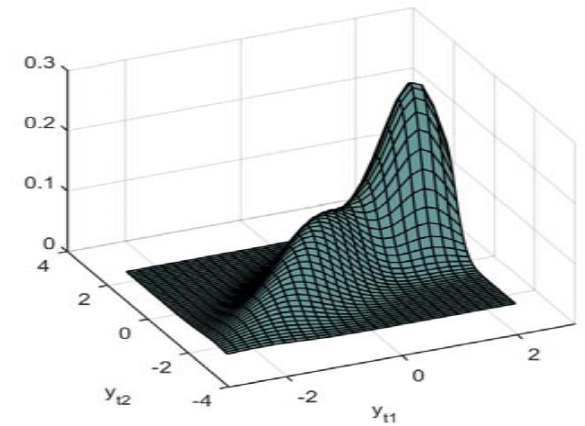
Model set:  $\mathcal{M}_{1:J}$

Predictions:

$$h_{tj}(\mathbf{y}_t)$$

Information:

$$\mathcal{H}_t = h_{t,1:J}(\cdot)$$



Predictive synthesis:  $p(\mathbf{y}_t | \mathcal{H}_t, \mathcal{I}_t)$

Past/prior information



$$p(\mathbf{y}_t | \mathcal{H}_t, \mathcal{I}_t) = \int \mathbf{x}_{t,1:J} \alpha_t(\mathbf{y}_t | \mathbf{x}_{t,1:J}) \prod_{j=1:J} h_{tj}(\mathbf{x}_{tj}) d\mathbf{x}_{tj}$$

Synthesis model/pdf

(Dynamic) latent agent factors

- *Model-specific biases, calibration*
- *Relative expertise/accuracy*
- *Model inter-dependencies*
- *Incomplete model set: Includes ability to “ignore” & adapt*
- *Time-variation ... in all the above*

- A subset of full Bayesian models (theory)
- Many choices of synthesis model/function



## A Few Comments on Bianchi & McAllin

- Nice idea: Models to be synthesised = Subset regressions (dynamic)

MW1

- Uniform predictive improvements (over lasso, BMA, etc) – why?
  - “illusion of sparsity” (high collinearities- avoid big models)
  - don’t select : mix over small models ... somehow
  - model set incompleteness: BPS “encompasses” and adapts
  - dynamics
- Forecast goals focus: Build models for a purpose
  - multi-step or path-ahead forecast goals
  - decision goals in other contexts
- Elucidates model/forecast interdependencies
  - ... and their dynamics over time

Slide 4

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MW1

prove

Mike West, 16/06/2018



- Aggregation of “weak learners”:
  - BART: (“boosting”) McCulloch et al, 2010 AAOS
  - Decision-guided SSS: MW et al 2004-10, JASA, JCGS
  - Lee & Clyde (“bagging”) 2004 JMLR
- Emergent linked themes:
  - Shephard, Engle et al 2014 (bagging: “Composite likelihood” - CL)
  - Chan, Koop et al 2018 – CL for large TV-VARs
    - mixing large numbers of small intersecting models
    - structurally – a special subclass of SGDLMs
- Decouple/Recouple: Rethinking modelling for scale-up  
SGDLMs: - decoupled sets of small univariate dynamic models
  - recoupled via (dynamic) simultaneous equations
  - G = graphical model underpinnings



Vector outcome  $\mathbf{y}_t = (y_{1t}, \dots, y_{mt})'$

$$y_{jt} \leftarrow \text{DLM}(\mathbf{x}_{jt}, \mathbf{y}_{sp(j),t}, v_{jt})$$

Series  $j$  specific predictors

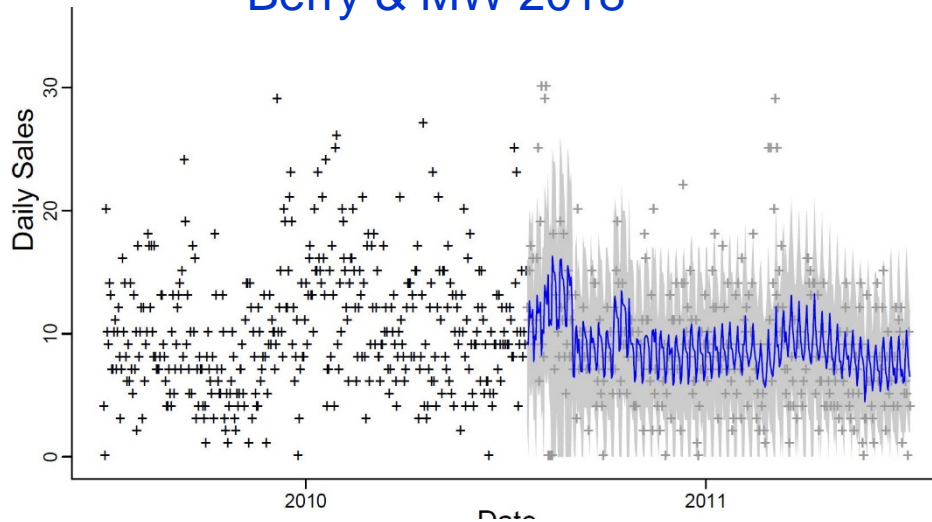
Simultaneous parental predictors

- *Contemporaneous & lagged directed graphical models*
- *Flexible, sparse multivariate volatility structure induced*
- *Efficient forward filtering & forecasting*
- *Scale-up with  $m$ : Decouple/recouple analysis -  $O(m)$*
- *Examples:  $m \sim 400$*
- *GPU implementation exemplar*

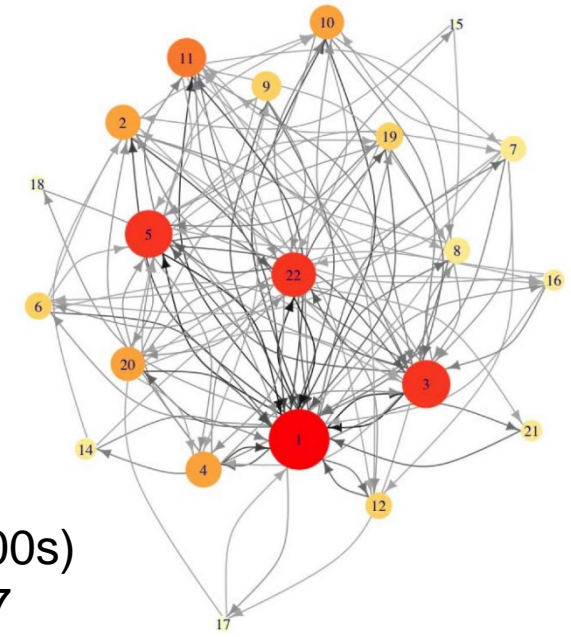
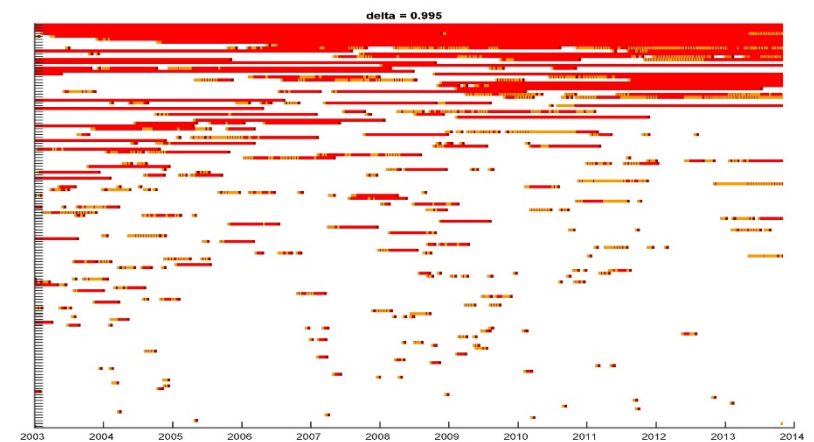


# Decouple/Recouple for Large Time Series

Multi-scale count series (000s)  
Berry & MW 2018



SGDLMs - finance/macro econ (00s)



Dynamic network flows (000s)  
Xi, MW et al, JASA 2017





## Bianchi & McAllin and DPR: A Few Questions

- Sum-to-one weights issue – irrelevant! (e.g., all  $\sim 0$ )
- How to choose small models?
  - theory/insights/economics
  - more details please
  - “overlay” with statistical ideas? Parsimony: “orthogonal” models?
- Go deeper with model interdependencies
  - changes over time: utility in informing interventions?
  - generating insights for model set refinements?
- Predictive improvements:
  - Time-varying BPS parameters: Role of dynamics



- Macro example (eg): 8 models to be synthesised
  - DLMS with “too many” predictors- stability? Sparser models
  - New thoughts: Hierarchical BPS ...?
- Key issues: multi-step ahead predictions
  - Univariate models require future values of predictors
  - Predict the predictors offline? (no mention in draft ....)
- Impulse response analysis & multi-step forecasting (for decisions)
  - Need multivariate models
  - SGDLMS-DPR models - Univariate DPRs coupled in SGDLMS?