# Bayesian Dependent Functional Mixture Estimation for Area and Time-Indexed Data: An Application for the Prediction of Monthly County Employment

Terrance D. Savitsky <sup>1</sup> Matthew R. Williams <sup>2</sup>

<sup>1</sup> U.S. Bureau of Labor Statistics (Office of Survey Methods Research)

<sup>2</sup>RTI International (Division for Statistical and Data Sciences)



Seasonal Adjustment Practitioners Workshop June 7-8, 2022

#### Outline

Motivation: LAUS Forecasts

Model: Four Major Components

Forecast Performance: Comparing Alternatives

#### Background

- ► Local Area Un/employment "survey" (LAUS) publishes by county
  - ► Employment and Unemployment totals
  - Monthly
  - ► For *every* county and Municipal Civil Division (MCD) in the U.S.
  - ▶ ... there is no survey.

# Background (2)

- ► LAUS project forward census instrument
  - Quarterly Census of Employment and Wages (QCEW)
  - ▶ by 7 months
  - for each county time series, separately
  - Includes seasonality
- Simultaneously model collection of county time-series
  - ► To produce more accurate predictions.

### LAUS Employment Estimation

- LAUS (Local Area Unemployment Survey) partners with States for county-level monthly employment
- ► CES (Current Employment Statistics) is unavailable for 1751 out of 3108 counties
- ► Partnering with QCEW (Quarterly Census of Employment and Wages) program to use lagged data and project forward 7 months
- ▶ Data set is  $N = 3108 \times T = 180$ ,
- i = 1, ..., (N = 3108) counties
- ▶ j = 1, ..., (T = 180) months
  - ▶ Observe Jan 2002 May 2016
  - ▶ Predict 7 months, June December 2016
- ▶ Project monthly values, by county, for remainder of 2016.

#### Outline

Motivation: LAUS Forecasts

Model: Four Major Components

Forecast Performance: Comparing Alternatives

# County-indexed Time Series

- $\qquad \qquad \mathbf{y}_{ij} \sim \mathcal{N}\left(f_{ij} = \mathbf{pred}_{ij} + \mathbf{tr}_{ij} + \mathbf{seas}_{ij}, \tau_y^{-1}\right)$
- $lackbox{pred}_{ij} = \mathbf{x}_{ij}^{'} oldsymbol{eta}_i; oldsymbol{eta}_i \sim \mathcal{N}_P\left(oldsymbol{\mu}_i, \Lambda_i^{-1}
  ight)$
- ightharpoonup T imes 1,  $\operatorname{tr}_i \sim f_{\nu_i}$ , autoregressive, bw  $1 \ (\operatorname{tr}_{i,j-1},\operatorname{tr}_{i,j+1})$ .

$$\operatorname{tr}_{i} \stackrel{\operatorname{ind}}{\sim} \nu_{i}^{\frac{T-1}{2}} \exp\left(-\frac{\nu_{i}}{2} \sum_{j=1}^{T-1} \left(\operatorname{tr}_{i(j+1)} - \operatorname{tr}_{ij}\right)^{2}\right) \tag{1}$$

$$=\nu_i^{\frac{T-1}{2}}\exp\left(-\frac{\nu_i}{2}\mathsf{tr}_i^TQ\mathsf{tr}_i\right) \tag{2}$$

- ▶ Precision matrix,  $Q = (D \Omega)$
- Rank-deficient since mean level not identified
- Probabilistic local smoother

### County-indexed Time Series

- $ightharpoonup y_{ij} \sim \mathcal{N}\left(f_{ij} = \operatorname{pred}_{ij} + \operatorname{tr}_{ij} + \operatorname{seas}_{ij}, \tau_y^{-1}\right)$
- ightharpoonup pred $_{ij}=\mathbf{x}_{ij}^{'}oldsymbol{eta}_{i};\,oldsymbol{eta}_{i}\sim\mathcal{N}_{P}\left(oldsymbol{\mu}_{i},\Lambda_{i}^{-1}
  ight)$
- ightharpoonup T imes 1,  $\operatorname{tr}_i \sim f_{\nu_i}$ , autoregressive, bw  $1 \ (\operatorname{tr}_{i,j-1},\operatorname{tr}_{i,j+1})$ .
- ▶ 2 options for  $T \times 1$ , seas<sub>i</sub>:
  - seas<sub>i</sub>  $\sim g_{\phi_i}$ , autoregressive, bw (O=12)-1 (seas<sub>ij</sub>,..., seas<sub>i(j+(O-1))</sub>)
    - ▶ Improper, local, seas<sub>i</sub> =  $\mathcal{N}_T \left( \mathbf{0}, Q_i^{-1} = \left[ \tau_i \left( D \Omega \right) \right]^{-1} \right)$
    - Proper, global seas<sub>i</sub> =  $\mathcal{N}_T \left( \mathbf{0}, Q_i^{-1} = \left[ \tau_i \left( D \rho_i \Omega \right) \right]^{-1} \right)$
  - $\begin{array}{l} \blacktriangleright \ \operatorname{seas}_{ij} = \operatorname{fourier\ basis} = \\ \begin{bmatrix} {}^{O-1\times 1} \\ \mathbf{z}_{ij} \end{bmatrix} = & \left\{ \cos\left(\frac{2\pi k_1 j}{O}\right), \sin\left(\frac{2\pi k_2 j}{O}\right) \right\}_{k_1 = 1, \ldots, O/2, \ k_2 = 1, \ldots, (O/2-1)} \end{bmatrix} \times \kappa_i \\ \blacktriangleright \ \mathbf{x}_{ij} \leftarrow (\mathbf{x}_{ij}, \mathbf{z}_{ij}) \ \operatorname{and} \ \boldsymbol{\beta}_i \leftarrow (\boldsymbol{\beta}_i, \kappa_i). \end{aligned}$

### County-indexed Time Series

- $\blacktriangleright y_{ij} \sim \mathcal{N}\left(f_{ij} = \operatorname{pred}_{ij} + \operatorname{tr}_{ij} + \operatorname{seas}_{ij}, \tau_y^{-1}\right)$
- ightharpoonup pred $_{ij}=\mathbf{x}_{ij}^{'}oldsymbol{eta}_{i};\,oldsymbol{eta}_{i}\sim\mathcal{N}_{P}\left(oldsymbol{\mu}_{i},\Lambda_{i}^{-1}
  ight)$
- ightharpoonup T imes 1,  $\operatorname{tr}_i \sim f_{\nu_i}$ , autoregressive, bw  $1 \ (\operatorname{tr}_{i,j-1},\operatorname{tr}_{i,j+1})$ .
- ▶ 2 options for  $T \times 1$ , seas<sub>i</sub>:
  - ▶ seas<sub>i</sub>  $\sim g_{\phi_i}$ , autoregressive, bw (O = 12) 1 (seas<sub>ij</sub>, . . . , seas<sub>i(j+(O-1))</sub>)
  - ► seas<sub>ij</sub> = fourier basis =  ${\mathbf{z}_{ij}^{O-1 \times 1}} \times \kappa_i$ ►  $\mathbf{x}_{ii} \leftarrow (\mathbf{x}_{ij}, \mathbf{z}_{ij})$  and  $\beta_i \leftarrow (\beta_i, \kappa_i)$ .
- Probabilistic Clustering:
  - ightharpoonup Collect,  $oldsymbol{ heta}_i = (
    u_i, \phi_i, oldsymbol{\mu}_i, \Lambda_i)$
  - ▶ Unique cluster parameter values,  $\theta_k^*$ ,  $k = 1, ..., K \le n$
  - ▶ If counties  $i, \ell \in \mathsf{cluster}\ k \to \pmb{\theta}_i = \pmb{\theta}_\ell = \pmb{\theta}_k^*$

# Predictors Used for Clustering

- ▶ location quotient  $\in [0,1]$ , employment concentration of economic sector in county compared to national average.
- ► Sectors constructed from the first 2— digits of detailed NAICS industry code
- Sectors: Construction, Transportation, Services, Leisure, Public, Mining, Manufacturing, Information, Education.
- Assertion: location quotient more useful than spatial contiguity.
  - e.g., Rural county adjacent to urban county
  - ► Distinct economic drivers / bases
- Other predictors:
  - Unemployment insurance (UI) claims in each month for each county to measure economic health.
  - ► Latitude and Longitude, computed based on population (rather than geographic) centroids

#### Outline

Motivation: LAUS Forecasts

Model: Four Major Components

Forecast Performance: Comparing Alternatives

### Compare Seasonality Methods: Less Expressed

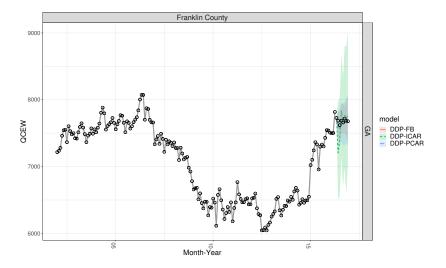


Figure: Fourier Basis (pink). Proper AR (blue), Local AR (green).

# Compare Seasonality Methods: More Expressed

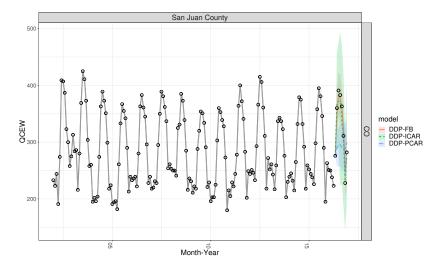


Figure: Fourier Basis (pink). Proper AR (blue), Local AR (green).

# Smaller County

► Little seasonality expressed

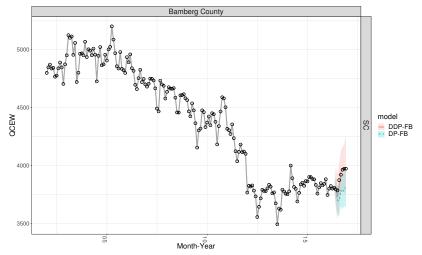


Figure: Predictor Assist (pink). Unsupervised (turquoise).

#### Medium-sized County

► Higher, but irregular seasonality expressed

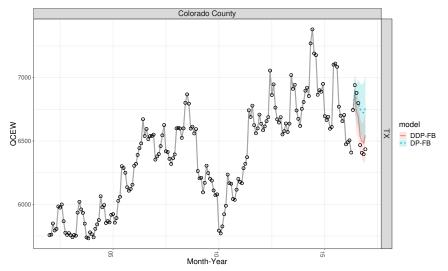


Figure: Predictor Assist (pink). Unsupervised (turquoise).

#### Tiny County

#### ► Fibrilation

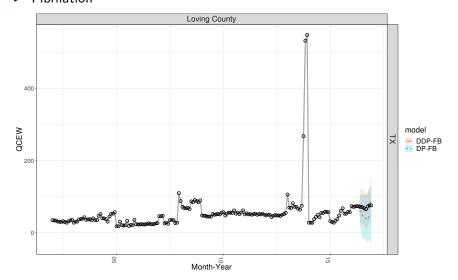


Figure: Predictor Assist (pink). Unsupervised (turquoise).

# Spatial Process vs. Time-series

Higher, but irregular seasonality expressed

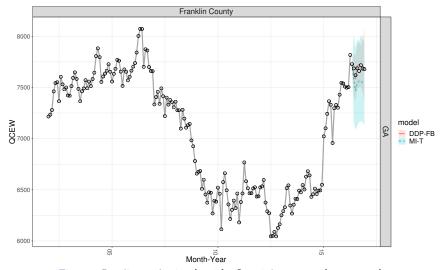


Figure: Predictor Assist (pink). Spatial process (turquoise).

### Compare Prediction Errors of Models

Model	RMSPE	MAPE-C
Predictor Ast. Fourier (DDP - FB)	919	1.29%
Unsupervised Fourier (DP - FB)	1570	2.11%
Predictor Ast. Global (DDP - PCAR)	1688	2.45%
Predictor Ast. Local (DDP - ICAR)	2103	2.71%
Spatial Model (MI-t)	2987	3.37%
LAUS Production (SAEE)		2.49%

#### Comments:

- ► The models differentiated on seasonality
- ► DDP-FB performs best
- ► SAEE is the current production model

#### Summary

Bayesian Analysis, Advance Publication 1-25 2021. https://doi.org/10.1214/21-BA1274

- ▶ Heterogeneity between counties for seasonal structures is a challenge
- ► The Fourier Basis shows marked improvement over Autoregressive Smoothers
- ► The Predictor Assisted clustering (DDP) shows marked improvement over unsupervised clustering (DP)
- Co-modelling time series leads to better prediction vs. modelling time series separately
- ► Clustering based on similar economic indices improves performance.
- Modelling a spatially-varying time series was much more effective than modelling a time-varying spatial process

#### Thanks to:

 Garret Schmitt, Tyler Bohnsack, Nic Aakre, Andrew Bean, Walter Sylva

#### CONTACT INFORMATION

Savitsky.Terrance@bls.gov mrwilliams@rti.org

Bayesian Analysis, Advance Publication 1-25 2021. https://doi.org/10.1214/21-BA1274