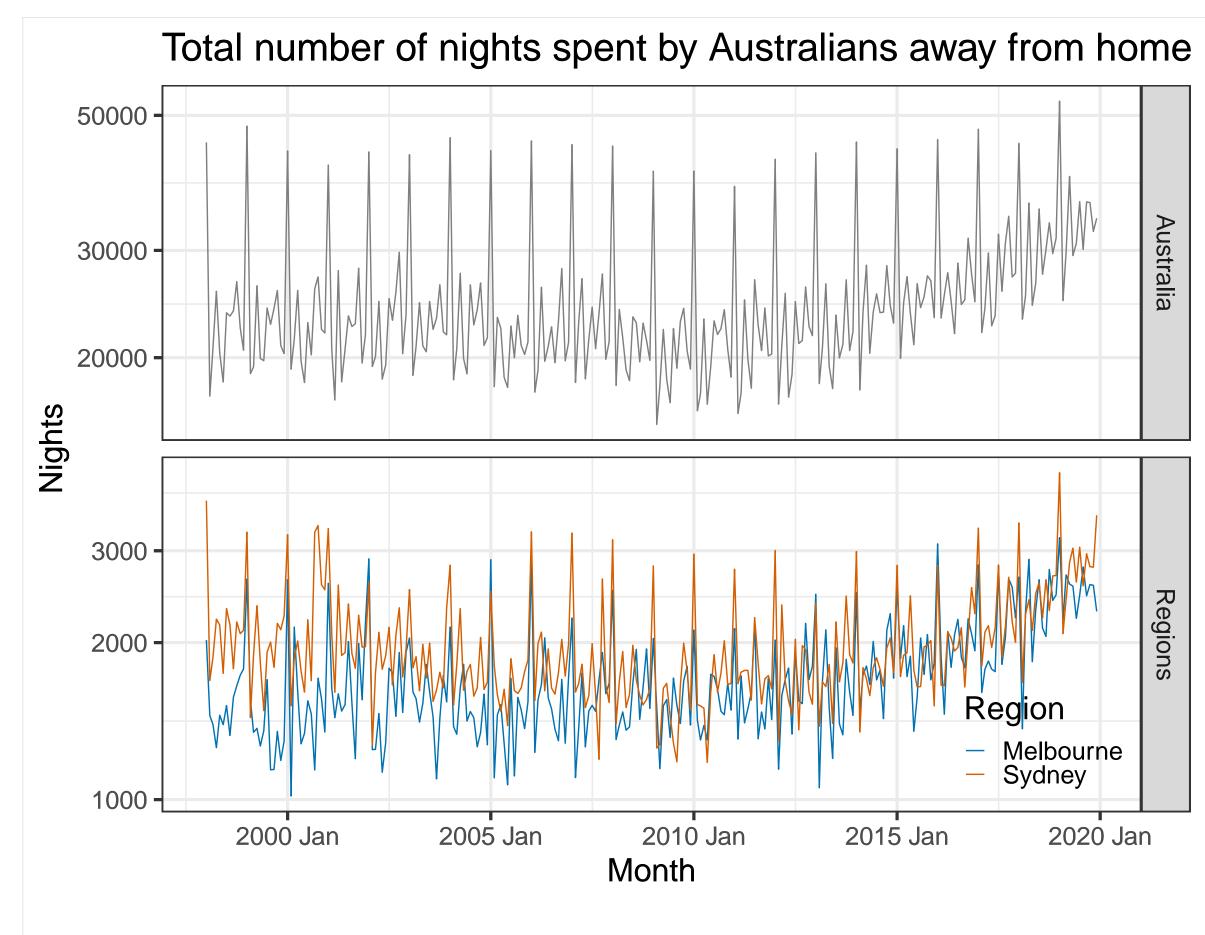
# T'ORECAST INFAR. AUGMENTED



We have multivariate time series:

- which share similar patterns;
- with a better signal-noise ratio in the linear combination

Can we find components that:

- 1. are easier to forecast;
- 2. can capture possible common signals;
- 3. can improve forecast of original series.

# A free lunch to reduce forecast error variance

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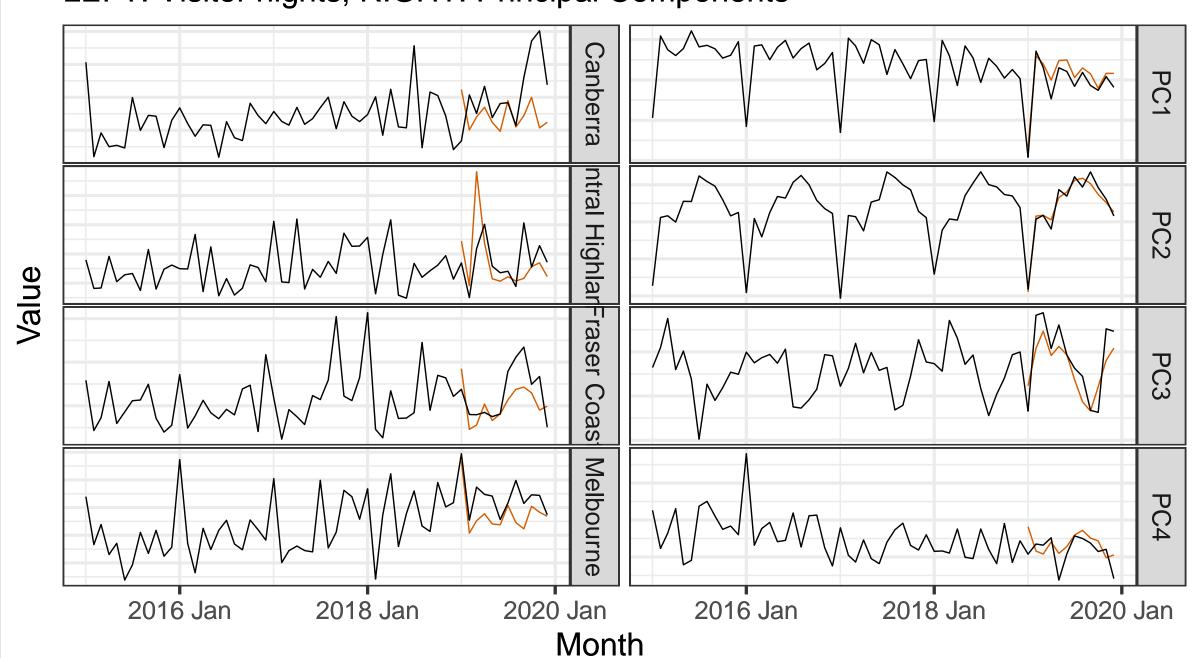
#### IMPLEMENTATION

Let  $y_t \in \mathbb{R}^m$  be a vector of m observed time series we are interested in forecasting. The FLAP method involves three steps:

- 1. Form components. Form  $c_t = \Phi y_t \in \mathbb{R}^p$ , a vector of p linear combinations of  $y_t$  at time t, where  $\Phi \in \mathbb{R}^{p \times m}$ . We call  $c_t$  the components of  $y_t$  and the component weights  $\Phi$  are known in the sense that they are chosen by the user of FLAP. Let  $\mathbf{z}_t = [\mathbf{y}_t', \mathbf{c}_t']'$  be the concatenation of series  $\mathbf{y}_t$  and components  $c_t$ .  $z_t$  will be constrained in the sense that  $Cz_t = c_t - \Phi y_t = 0$  for any t where  $C = \begin{bmatrix} -\Phi & I_p \end{bmatrix}$  is referred to as the constraint matrix.
- 2. Generate forecasts. Denote as  $\hat{z}_{t+h}$  the h-step-ahead base forecast of  $z_t$ . The method used to generate forecasts is again selected by the user, and **any** prediction method can be used.

#### History and Base Forecast

LEFT: Visitor nights; RIGHT: Principal Components



3. Project the base forecasts. Let  $\tilde{z}_{t+h}$  be a set of projected forecasts such that,

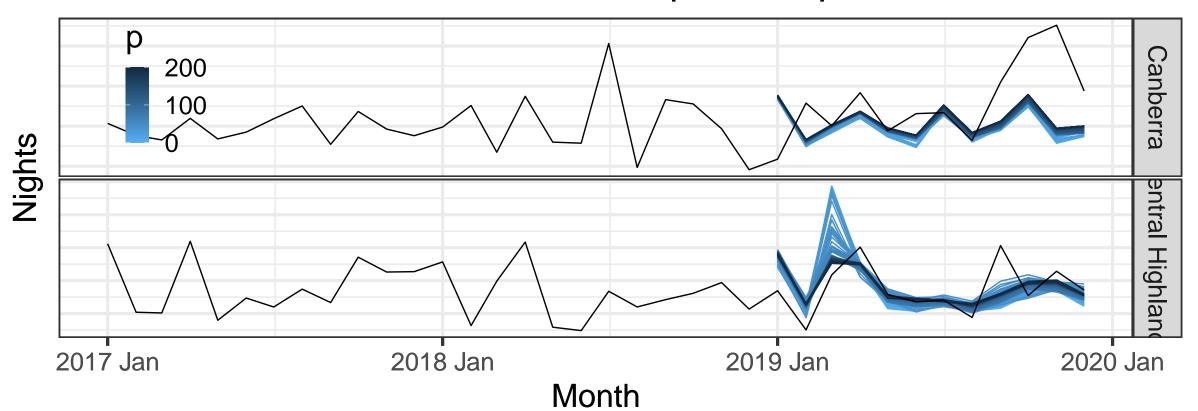
$$\tilde{\boldsymbol{z}}_{t+h} = \boldsymbol{M}\hat{\boldsymbol{z}}_{t+h} \tag{1}$$

with projection matrix

$$\boldsymbol{M} = \boldsymbol{I}_{m+p} - \boldsymbol{W}_h \boldsymbol{C}' (\boldsymbol{C} \boldsymbol{W}_h \boldsymbol{C}')^{-1} \boldsymbol{C}, \tag{}$$

where  $Var(\boldsymbol{z}_{t+h} - \hat{\boldsymbol{z}}_{t+h}) = \boldsymbol{W}_h$  is the forecast error covariance matrix. In practice a plug-in estimate can be used.

### FLAP forecasts with number of components p



# THEORITICAL PROPERTIES

#### Key results

semi-definite:

$$Var(\mathbf{y}_{t+h} - \hat{\mathbf{y}}_{t+h}) - Var(\mathbf{y}_{t+h} - \tilde{\mathbf{y}}_{t+h})$$

$$= \mathbf{J} \mathbf{W}_h \mathbf{C}' (\mathbf{C} \mathbf{W}_h \mathbf{C}')^{-1} \mathbf{C} \mathbf{W}_h \mathbf{J}'$$

2. The forecast error variance **monotonically** de- $\mathbf{W}_{v,h} = \text{Var}(\mathbf{y}_{t+h} - \hat{\mathbf{y}}_{t+h})$ , and  $\mathbf{w}_{c_1y,h}$  is the forecast creases with increasing number of components. The error covariance between the first component and diagonal elements of

$$Var(\boldsymbol{y}_{t+h} - \hat{\boldsymbol{y}}_{t+h}) - Var(\boldsymbol{y}_{t+h} - \tilde{\boldsymbol{y}}_{t+h})$$

$$= \boldsymbol{J}\boldsymbol{W}_{h}\boldsymbol{C}'(\boldsymbol{C}\boldsymbol{W}_{h}\boldsymbol{C}')^{-1}\boldsymbol{C}\boldsymbol{W}_{h}\boldsymbol{J}'$$

is non-decreasing as p increases.

3. The forecast projection is **optimal** to achieve minimum forecast error variance of each series. The projection is equivalent to the mapping

$$\tilde{\boldsymbol{y}}_{t+h} = \boldsymbol{G}\hat{\boldsymbol{z}}_{t+h},$$
 where  $\boldsymbol{G} = \begin{bmatrix} \boldsymbol{g}_1 & \boldsymbol{g}_2 & \dots & \boldsymbol{g}_m \end{bmatrix}' \in \mathbb{R}^{m \times (m+p)}$  is the solution to

 $rg \min m{GW_hG'}$ s.t.  $\boldsymbol{GS} = \boldsymbol{I}$ 

$$\underset{\boldsymbol{g}_{i}}{\operatorname{arg\,min}} \; \boldsymbol{g}_{i}' \boldsymbol{W}_{h} \boldsymbol{g}_{i} \qquad \text{s.t. } \boldsymbol{g}_{i}' \boldsymbol{s}_{j} = \boldsymbol{1}(i=j),$$

where 
$$m{S} = egin{bmatrix} m{I}_m \\ m{\Phi} \end{bmatrix} = m{igg[} m{s}_1 \cdots m{s}_m m{igg]}.$$

#### Positive condition

The forecast error variance is **reduced** with For the first component to have a **guaranteed** FLAP. The variance reduction matrix is positive reduction of forecast error variance, the following condition must be satisfied:

$$oldsymbol{\phi}_1 oldsymbol{W}_{y,h} 
eq oldsymbol{w}_{c_1 y,h},$$

where  $\phi_1$  is the weight vector of the first component, the original series.

A new component reduces the error variance as long as the its forecast covariance with the original series cannot be expressed as a linear combination of the forecast covariance between the already existing time series, in which case it adds no information.

## Example $W_h = I_{m+p}$

$$Var(\boldsymbol{y}_{t+h} - \hat{\boldsymbol{y}}_{t+h}) - Var(\boldsymbol{y}_{t+h} - \tilde{\boldsymbol{y}}_{t+h})$$

$$= \boldsymbol{J}\boldsymbol{C}'(\boldsymbol{C}\boldsymbol{C}')^{-1}\boldsymbol{C}\boldsymbol{J}'$$

$$= \boldsymbol{\Phi}'(\boldsymbol{\Phi}\boldsymbol{\Phi}' + \boldsymbol{I})^{-1}\boldsymbol{\Phi}$$

Let  $\Phi$  consist of orthogonal unit vectors:

 $\mathbf{\Phi}\mathbf{\Phi}' = \mathbf{I}_p \text{ when } p \leq m$ 

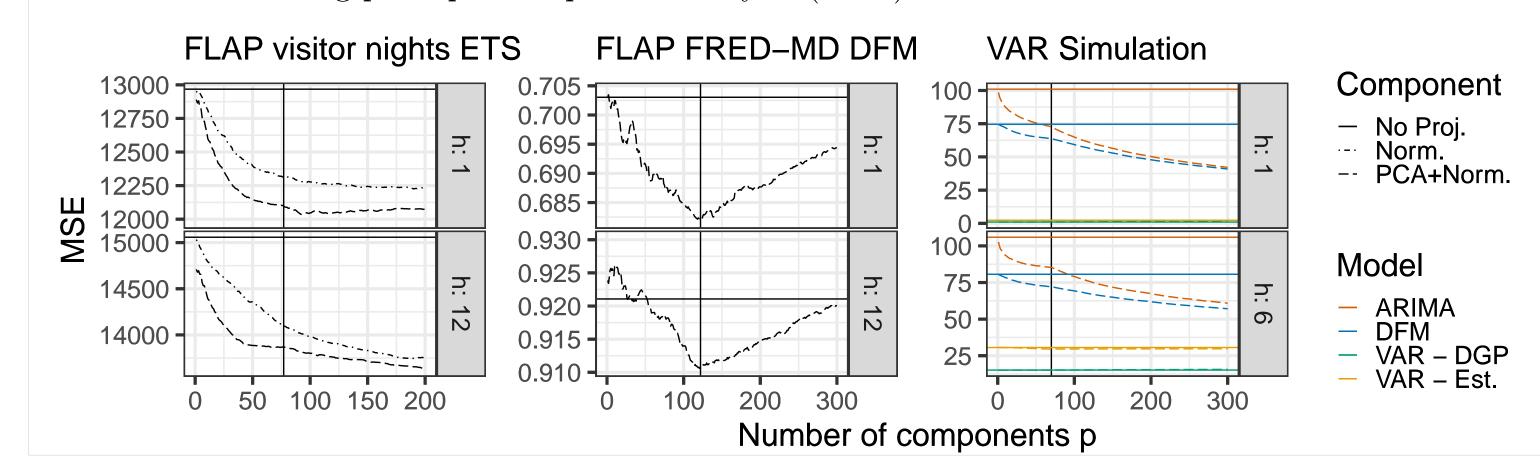
 $\Phi'\Phi = I_m \text{ when } p = m.$ 

$$\operatorname{tr}(\operatorname{Var}(\boldsymbol{y}_{t+h} - \hat{\boldsymbol{y}}_{t+h}) - \operatorname{Var}(\boldsymbol{y}_{t+h} - \tilde{\boldsymbol{y}}_{t+h}))$$
$$= \frac{1}{2} \operatorname{tr}(\boldsymbol{\Phi}' \boldsymbol{\Phi}) = \frac{1}{2} p$$

# APPLICATIONS

or

We estimate  $W_h$  using a shrinkage estimator to ensure positive definitness and numerical stability. We construct  $\Phi$  using principal component analysis (PCA) and simulations from random distributions.



## R package availabe on CRAN! install.packages("flap")

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**Projection matrix** The matrix M is a projection onto the space where the constraint  $Cz_t = 0$  is satisfied.

