A classification framework for forecast-model selection

Thiyanga S Talagala
Rob J Hyndman
George Athanasopoulos

Monash University, Australia
Slides: http://thiyanga.netlify.com/talk/jsm18-talk/

Joint Statistical Meetings, 2018


You Tube


TransWood
TransAtlantic

Time series features

Objective

Develop a framework that automates the selection of the most appropriate forecasting method for a given time series by using an array of features computed from the time series.

Time series features

Objective

Develop a framework that automates the selection of the most appropriate forecasting method for a given time series by using an array of features computed from the time series.

- **Basic idea:**
  Transform a given time series $y = \{y_1, y_2, \cdots, y_n\}$ to a feature vector $F = (f_1(y), f_2(y), \cdots, f_p(y))'$.

Time series features

Objective

Develop a framework that automates the selection of the most appropriate forecasting method for a given time series by using an array of features computed from the time series.

- **Basic idea:**
  Transform a given time series $y = \{y_1, y_2, \cdots, y_n\}$ to a feature vector $F = (f_1(y), f_2(y), \cdots, f_p(y))'$.
- Examples for time series features

Time series features

Objective

Develop a framework that automates the selection of the most appropriate forecasting method for a given time series by using an array of features computed from the time series.

- **Basic idea:**
  Transform a given time series $y = \{y_1, y_2, \cdots, y_n\}$ to a feature vector $F = (f_1(y), f_2(y), \cdots, f_p(y))'$.
- Examples for time series features
  - strength of trend

Time series features

Objective

Develop a framework that automates the selection of the most appropriate forecasting method for a given time series by using an array of features computed from the time series.

- **Basic idea:**
  Transform a given time series $y = \{y_1, y_2, \cdots, y_n\}$ to a feature vector $F = (f_1(y), f_2(y), \cdots, f_p(y))'$.
- Examples for time series features
  - strength of trend
  - strength of seasonality

Time series features

Objective

Develop a framework that automates the selection of the most appropriate forecasting method for a given time series by using an array of features computed from the time series.

- **Basic idea:**
  Transform a given time series $y = \{y_1, y_2, \cdots, y_n\}$ to a feature vector $F = (f_1(y), f_2(y), \cdots, f_p(y))'$.
- Examples for time series features
  - strength of trend
  - strength of seasonality
  - lag-1 autocorrelation

Time series features

Objective

Develop a framework that automates the selection of the most appropriate forecasting method for a given time series by using an array of features computed from the time series.

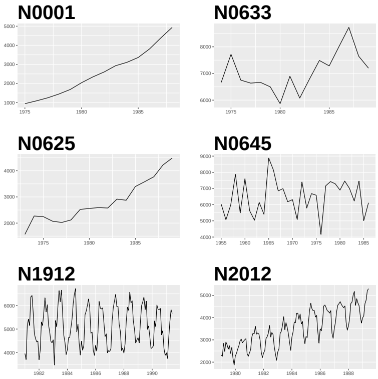
- **Basic idea:**
  Transform a given time series $y = \{y_1, y_2, \cdots, y_n\}$ to a feature vector $F = (f_1(y), f_2(y), \cdots, f_p(y))'$.
- Examples for time series features
  - strength of trend
  - strength of seasonality
  - lag-1 autocorrelation
  - spectral entropy

Feature-space of time series

STL-decomposition

$$Y_t = T_t + S_t + R_t$$

- strength of trend: $1 - \frac{Var(R_t)}{Var(Y_t - S_t)}$
- strength of seasonality: $1 - \frac{Var(R_t)}{Va(Y_t - T_t)}$

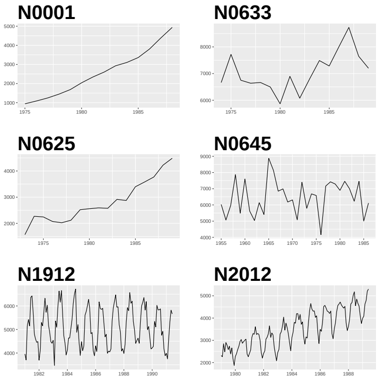


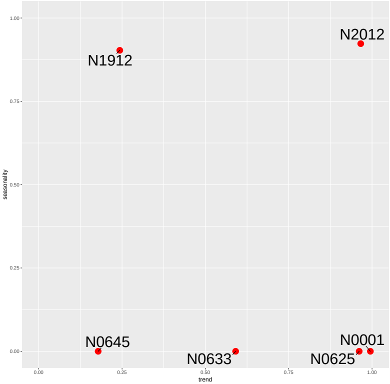
Feature-space of time series

STL-decomposition

$$Y_t = T_t + S_t + R_t$$

- strength of trend: $1 - \frac{Var(R_t)}{Var(Y_t - S_t)}$
- strength of seasonality: $1 - \frac{Var(R_t)}{Va(Y_t - T_t)}$





Time series features

- length
- strength of seasonality
- strength of trend
- linearity
- curvature
- spikiness
- stability
- lumpiness
- first ACF value of remainder series
- parameter estimates of Holt's linear trend method
- spectral entropy
- Hurst exponent
- nonlinearity
- parameter estimates of Holt-Winters' additive method
- unit root test statistics
- first ACF value of residual series of linear trend model
- ACF and PACF based features - calculated on both the raw and differenced series

Methodology: FFORMS

FFORMS: Feature-based **FOR**ecast **M**odel **S**election

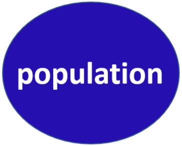
Offline

- A classification algorithm (the meta-learner) is trained.

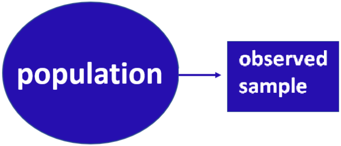
Online

- Calculate the features of a time series and use the pre-trained classifier to identify the best forecasting method.

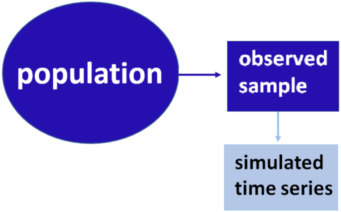
FFORMS: population



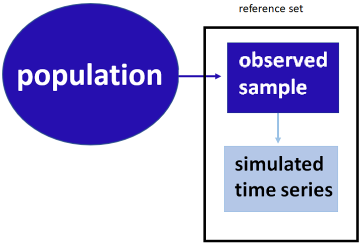
FFORMS: observed sample



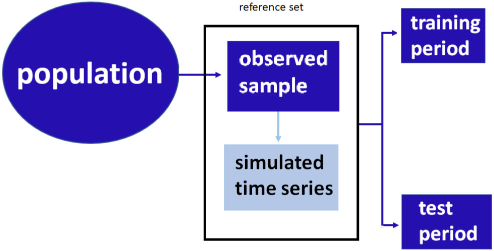
FFORMS: simulated time series



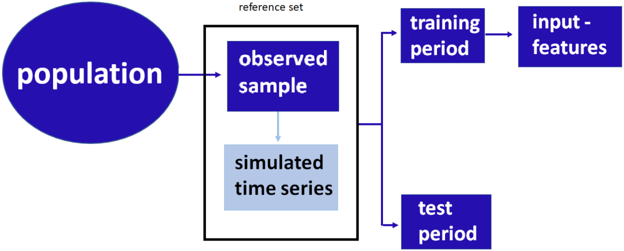
FFORMS: reference set



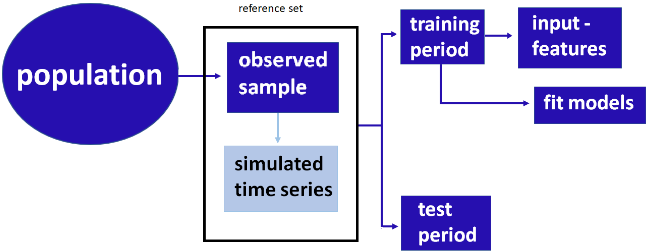
FFORMS: Meta-data



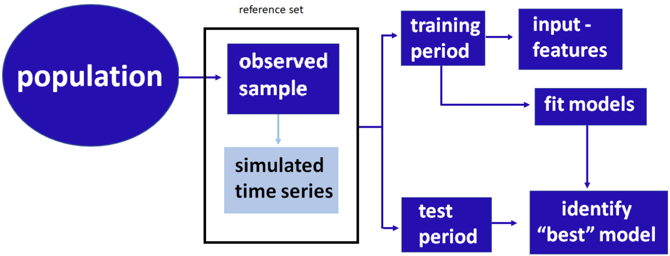
FFORMS: Meta-data



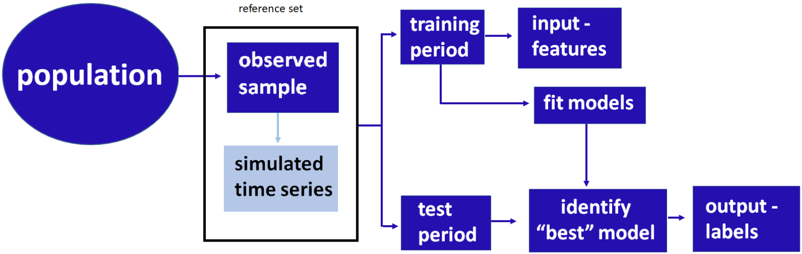
FFORMS: Meta-data



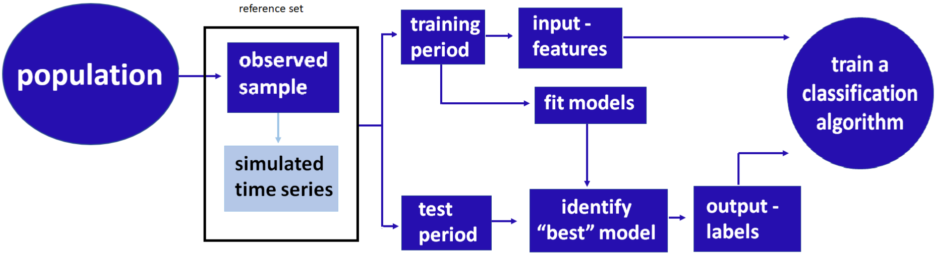
FFORMS: Meta-data



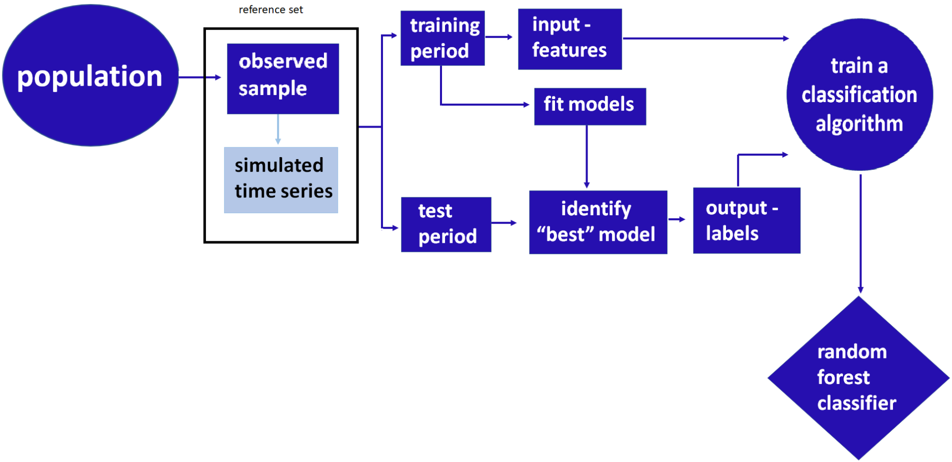
FFORMS: Meta-data



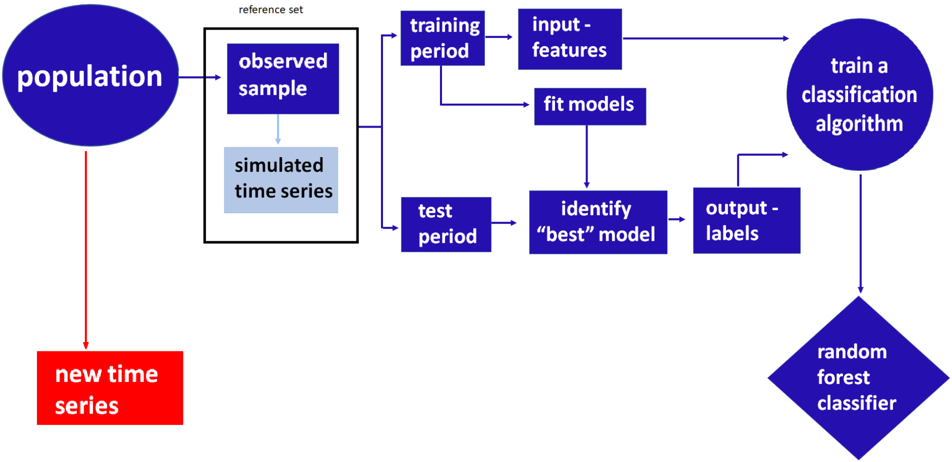
FFORMS: Meta-data



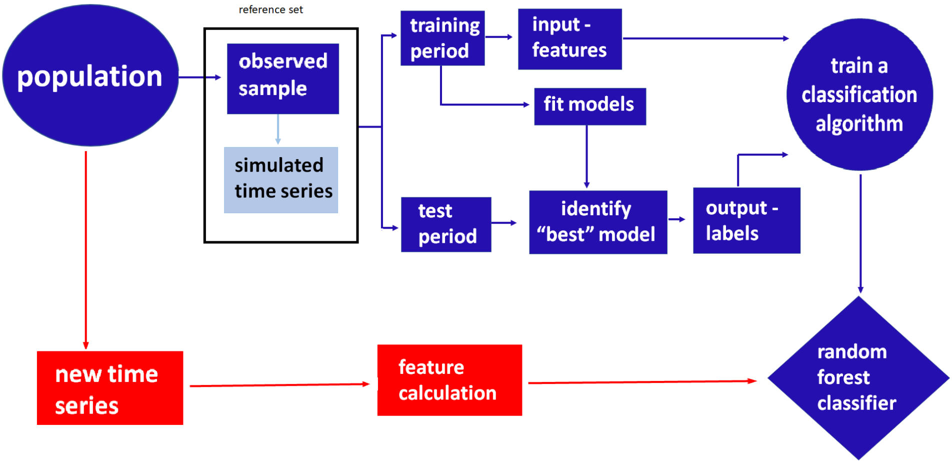
FFORMS: Random-forest classifier



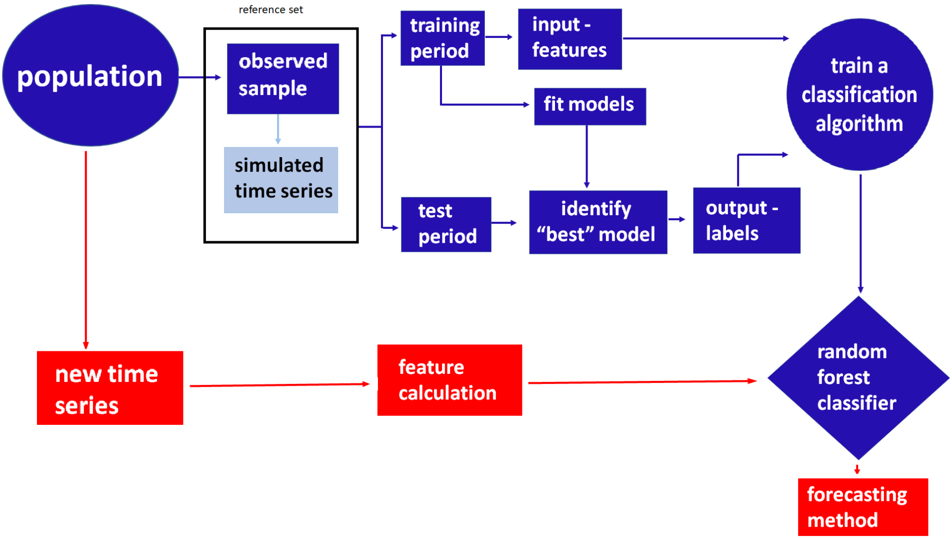
FFORMS: "online" part of the algorithm



FFORMS: “online” part of the algorithm



FFORMS: “online” part of the algorithm



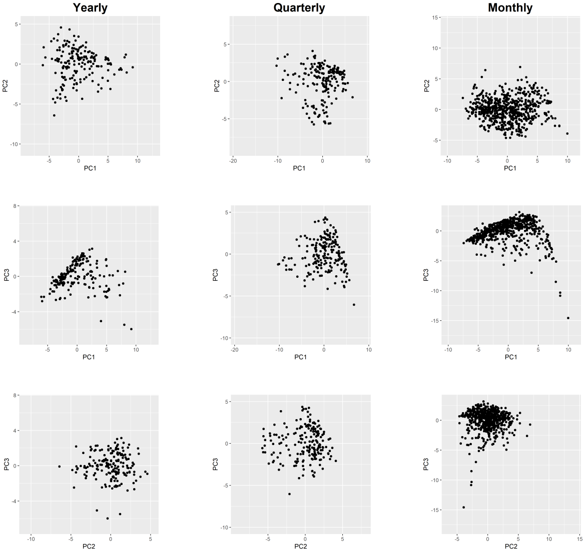
Application to M competition data

- Proposed algorithm is applied to yearly, quarterly and monthly series separately.
- We run two experiments for each case.

	Experiment 1				Experiment 2			
	Source	Y	Q	M	Source	Y	Q	M
Observed series	M1	181	203	617	M3	645	756	1428
Simulated series		362000	406000	123400		1290000	1512000	285600
New series	M3	645	756	1428	M1	181	203	617

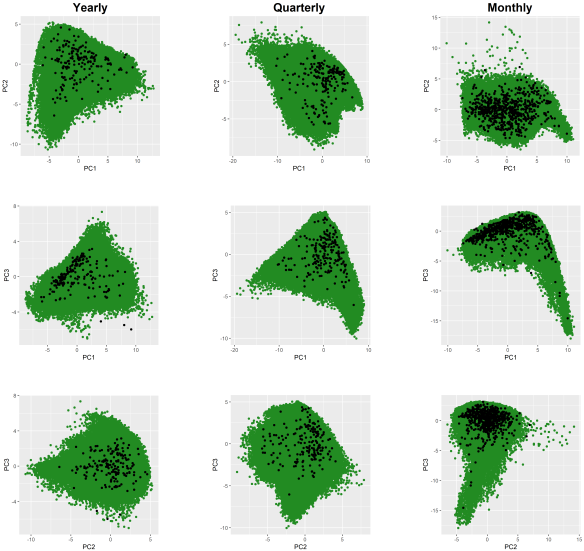
Experiment 1: Distribution of time series in the PCA space

observed - M1



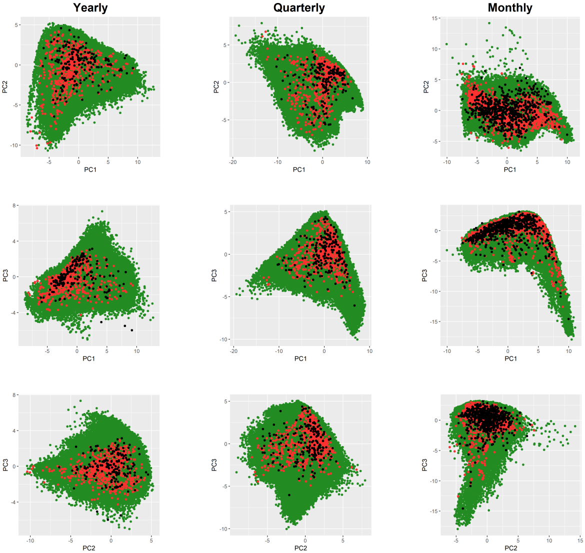
Experiment 1: Distribution of time series in the PCA space

observed - M1 simulated



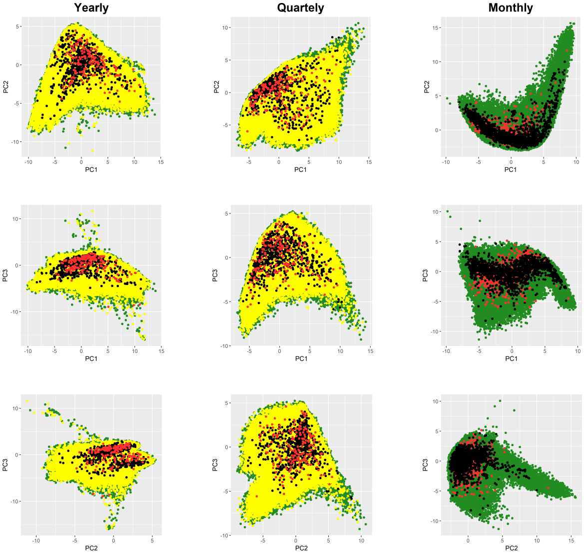
Experiment 1: Distribution of time series in the PCA space

observed - M1 | simulated | new - M3

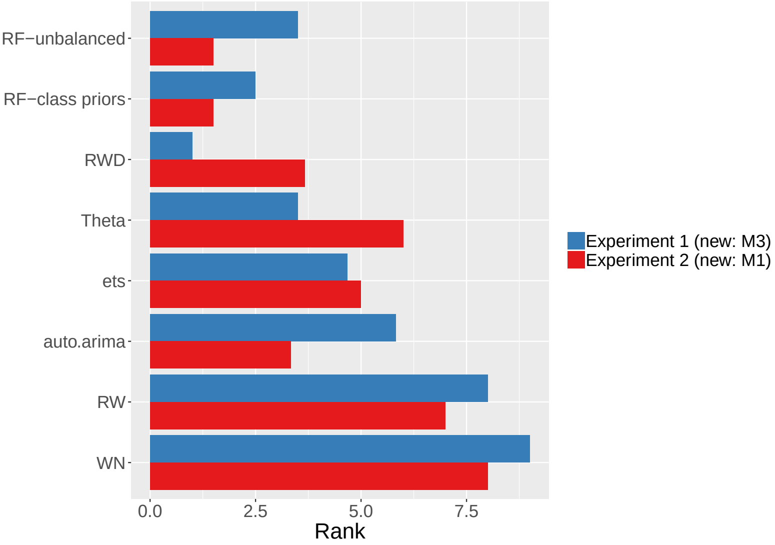


Experiment 2: Distribution of time series in the PCA space

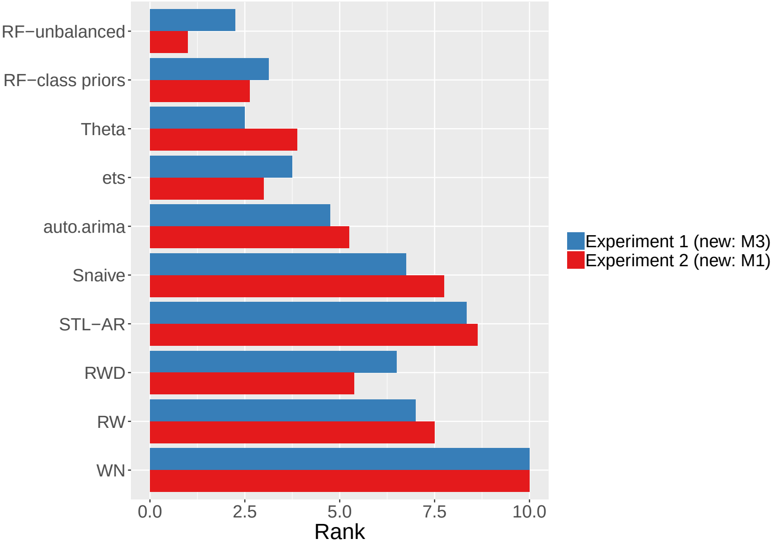
observed - M3 | simulated | subset | new - M1



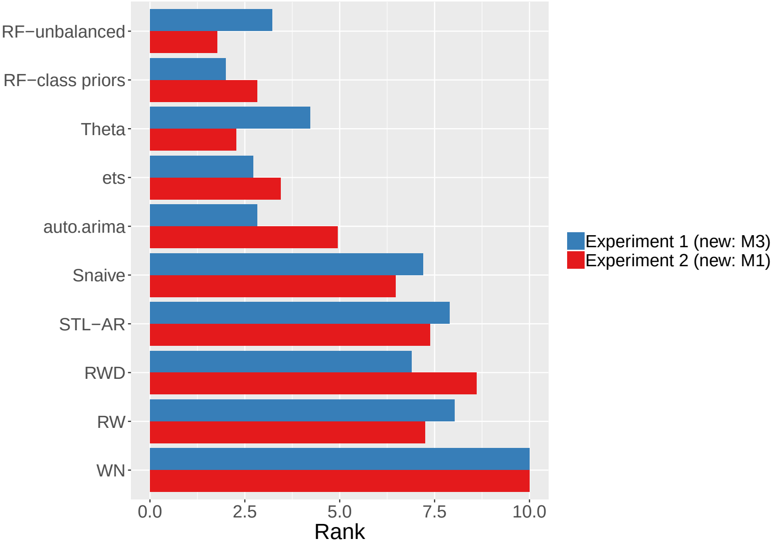
Results: Yearly



Results: Quarterly



Results: Monthly



Discussion and Conclusions

- FFORMS: framework for forecast model selection using meta-learning based on time series features.

Discussion and Conclusions

- FFORMS: framework for forecast model selection using meta-learning based on time series features.
- FFORMS algorithm uses the knowledge of the past performance of candidate forecast models on a collection of time series in order to identify the best forecasting method for a new series.

Discussion and Conclusions

- FFORMS: framework for forecast model selection using meta-learning based on time series features.
- FFORMS algorithm uses the knowledge of the past performance of candidate forecast models on a collection of time series in order to identify the best forecasting method for a new series.
- For real-time forecasting, our framework involves only the calculation of features, the selection of a forecast method based on the FFORMS random forest classifier, and the calculation of the forecasts from the chosen model.

Discussion and Conclusions

- FFORMS: framework for forecast model selection using meta-learning based on time series features.
- FFORMS algorithm uses the knowledge of the past performance of candidate forecast models on a collection of time series in order to identify the best forecasting method for a new series.
- For real-time forecasting, our framework involves only the calculation of features, the selection of a forecast method based on the FFORMS random forest classifier, and the calculation of the forecasts from the chosen model.
- We have also introduced a simple set of time series features that are useful in identifying the "best" forecast method for a given time series.

R package: seer

available at: https://github.com/thiyangt/seer

Installation

```r
devtools::install_github("thiyangt/seer")
library(seer)
```

R package: seer

available at: https://github.com/thiyangt/seer

Installation

```
devtools::install_github("thiyangt/seer")
library(seer)
```

paper: https://robjhyndman.com/publications/fforms/

email: thiyanga.talagala@monash.edu