Meta-learning how to forecast time series

Thiyanga S. Talagala
Rob J Hyndman
George Athanasopoulos

Monash University, Australia

Large collections of time series

- Forecasting demand for thousands of products across multiple warehouses.

Time series features

Objective

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

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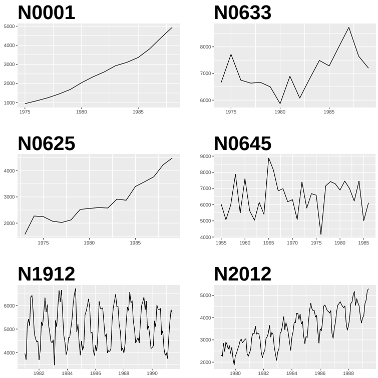
  - strength of seasonality
  - lag-1 autocorrelation
  - spectral entropy

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: $1 - \frac{Var(R_t)}{Va(Y_t - T_t)}$



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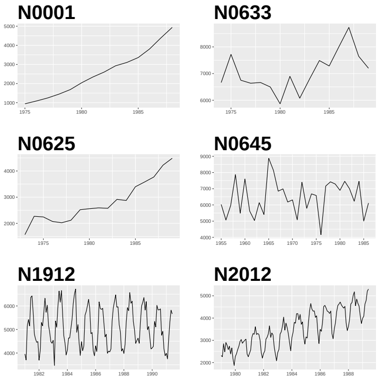
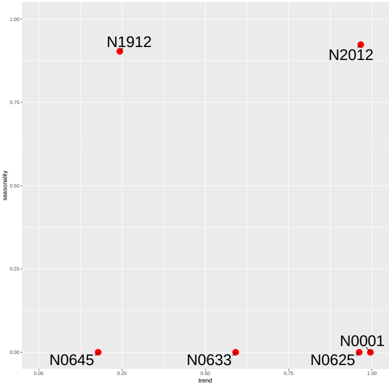




Time series features

- 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

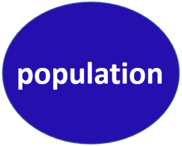
Methodology: FFORMS

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

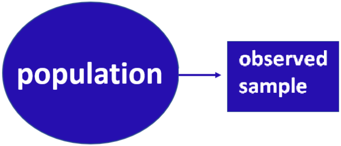
Offline: Classification algorithm is trained

Online: Use the classification algorithm to select appropriate forecast-models for new time series

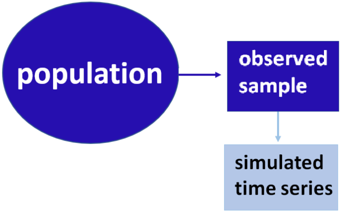
FFORMS: population



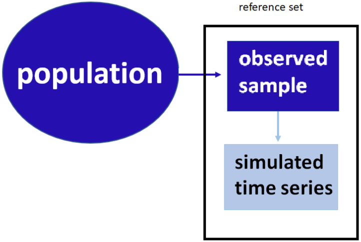
FFORMS: observed sample



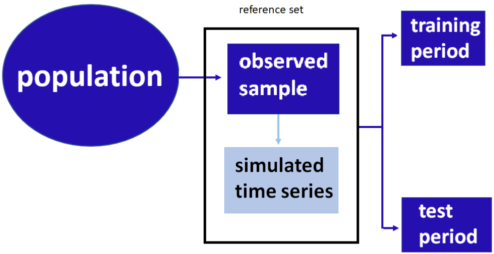
FFORMS: simulated time series



FFORMS: reference set



FFORMS: Meta-data



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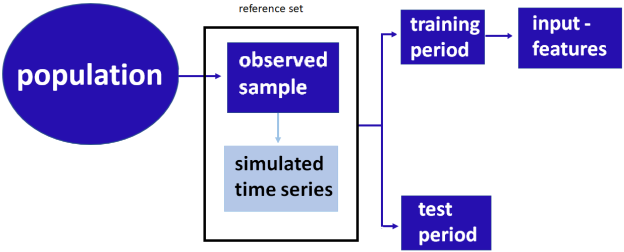

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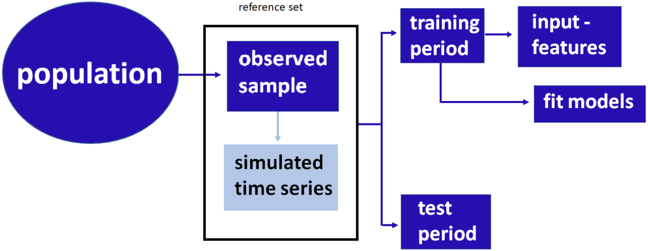

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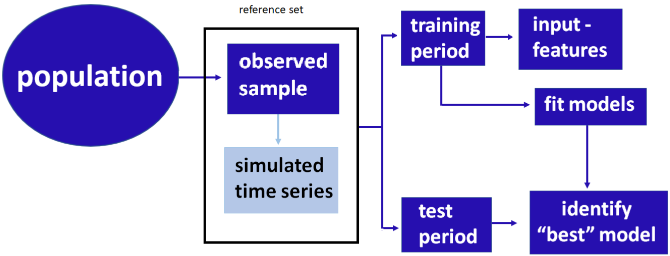

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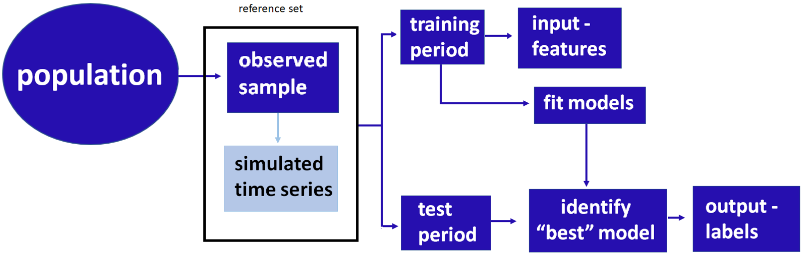

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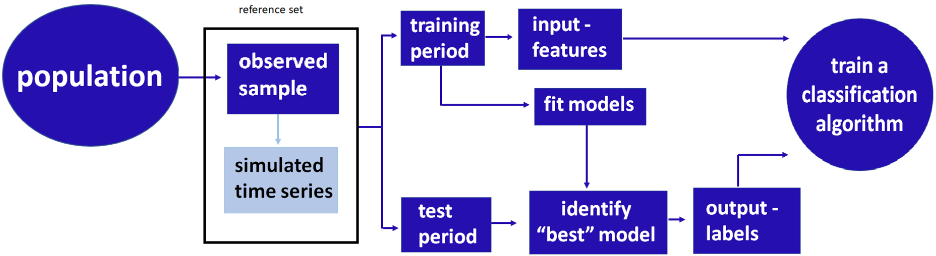
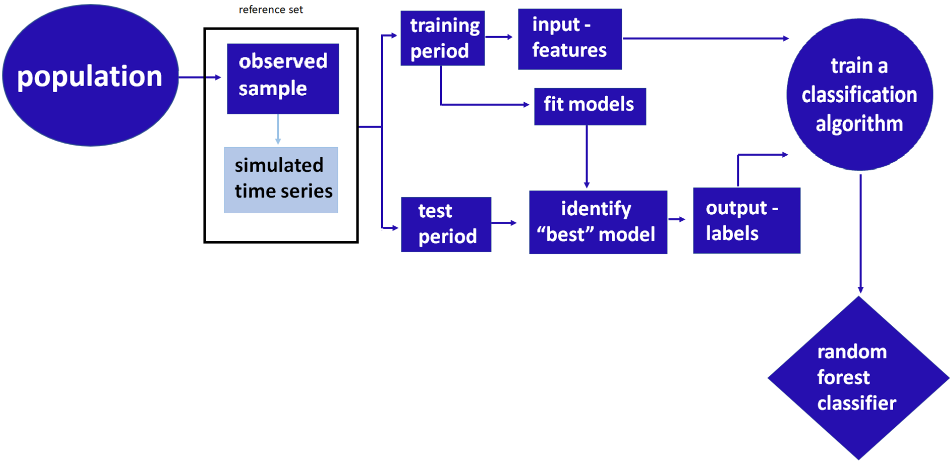
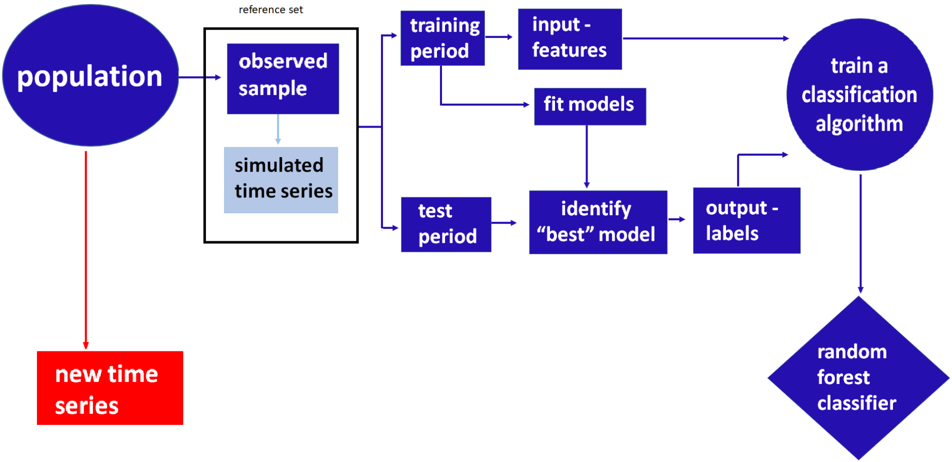


FFORMS: Random-forest classifier



FFORMS: "online" part of the algorithm



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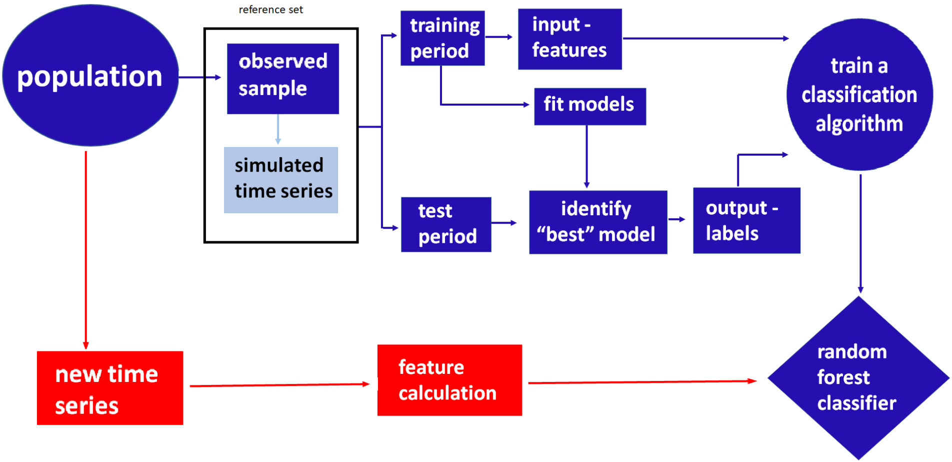

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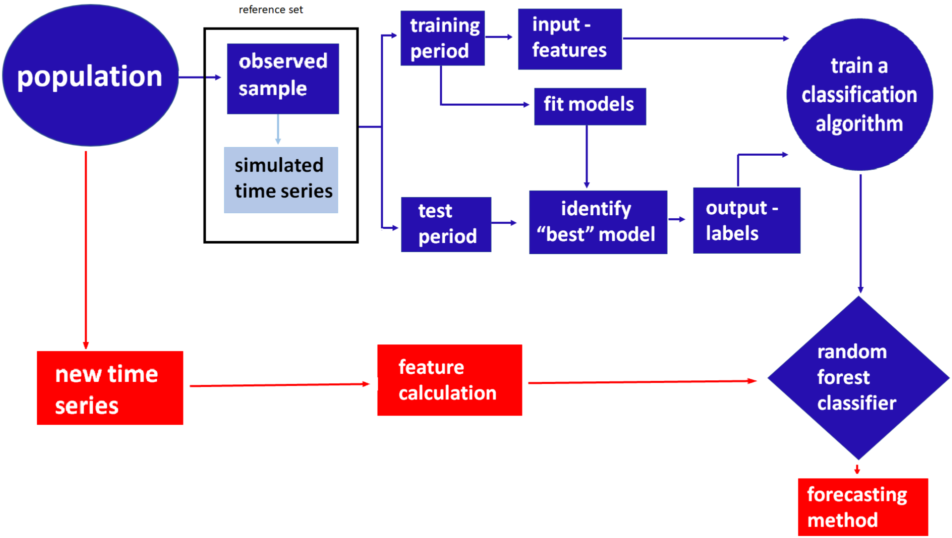


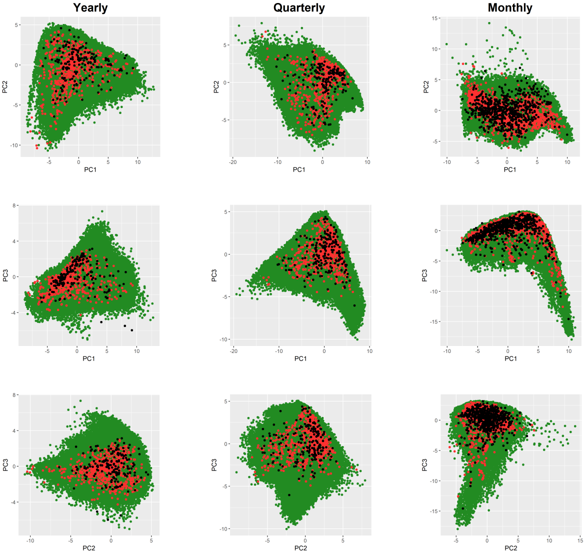
Application to M competition data

- 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

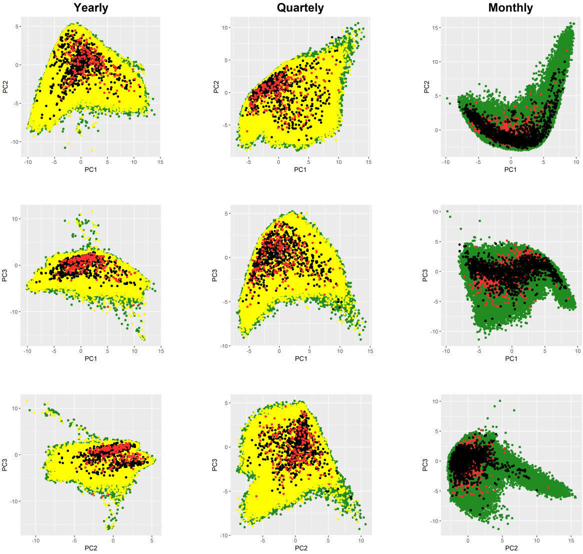
Experiment 1: Distribution of time series in the PCA space

observed - M1 simulated new - M3

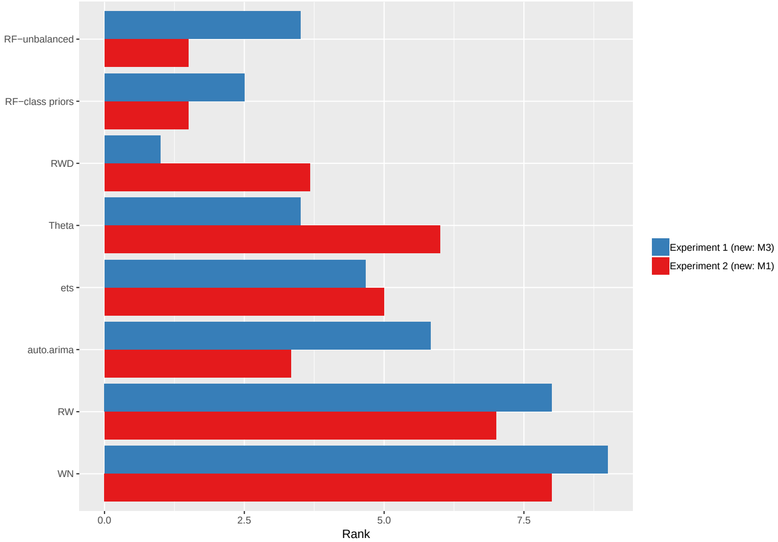


Experiment 2: Distribution of time series in the PCA space

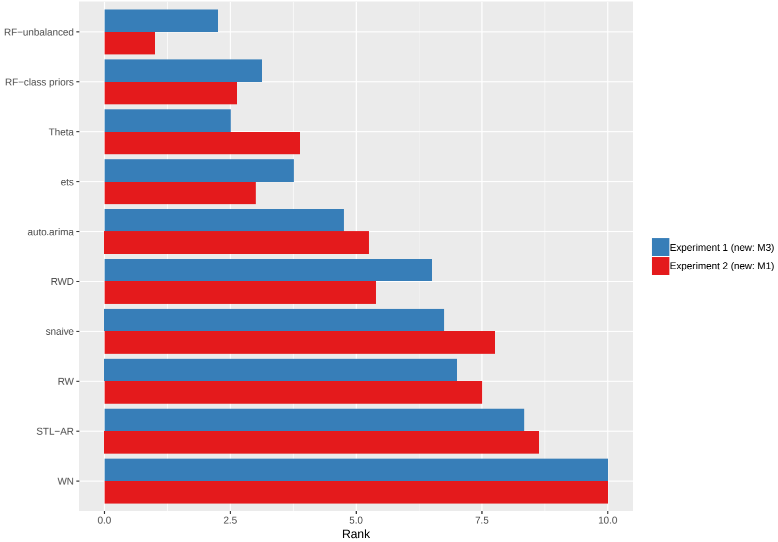
observed - M3 | simulated | subset | new - M1



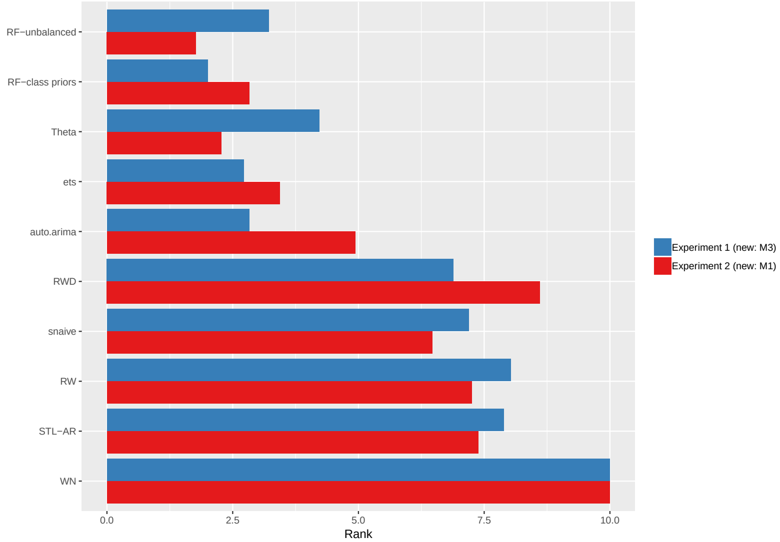
Results: Yearly



Results: Quarterly



Results: Monthly



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- Our method almost always performs better than common benchmark methods, and better than the best-performing methods from the M3 competition.
- The framework is general and can be applied to any large collection of time series.
- Advantage: Not necessary to estimate several different models for the data and undertake an empirical evaluation of their forecast accuracy on a given time series.

R package: seer

available at:

https://github.com/thiyangt/seer

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Reference: Talagala, TS, RJ Hyndman & G Athanasopoulos (2018). Meta-learning how to forecast time series. Technical Report 6/18, Monash University.