# Meta-learning how to forecast time series

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# Large collections of time series



• Forecasting demand for thousands of products across multiple warehouses.

#### Objective

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  - strength of trend

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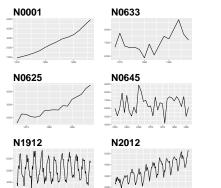
- Examples for time series features
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  - strength of seasonality
  - lag-1 autocorrelation
  - spectral entropy

# Feature-space of time series

### STL-decomposition

$$Y_t = T_t + S_t + R_t$$

- strength of trend:  $1 \frac{Var(R_t)}{Var(Y_t S_t)}$
- ullet strength of seasonality:  $1-rac{ extstyle ex$

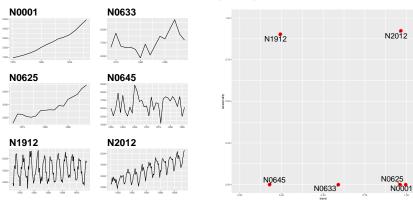


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- length
- strength of seasonality
- strength of trend
- linearity
- curvature
- spikiness
- stability
- lumpiness
- first ACF value of remainder series
- parameter estimates of Holt's linear trend method

- 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 FORecast Model Selection

Offline: Classification algorithm is trained

Online: Use the classification algorithm to select appropriate

forecast-models for new time series

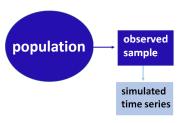
# FFORMS: population



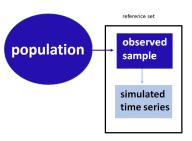
# FFORMS: observed sample

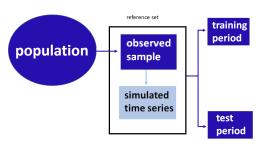


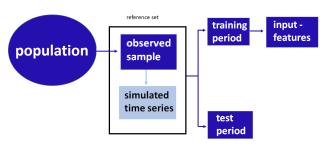
# FFORMS: simulated time series

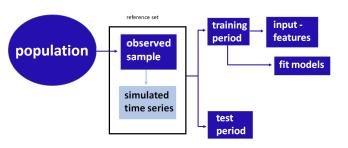


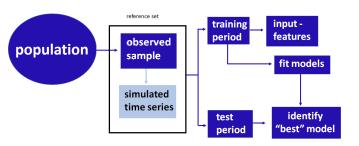
# FFORMS: reference set

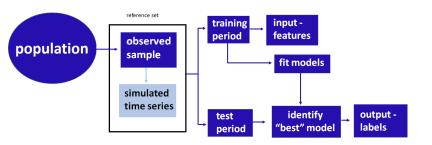


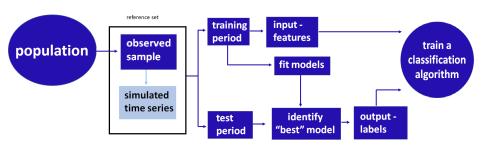




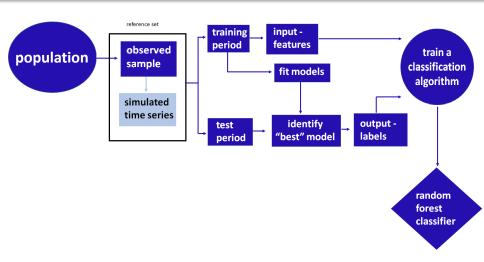




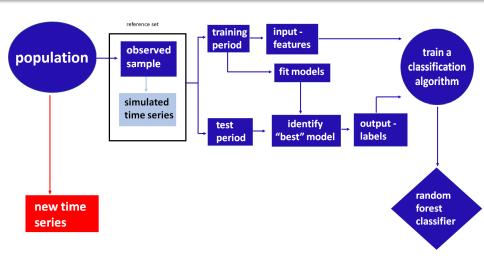




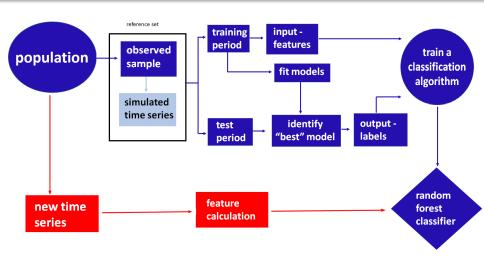
## FFORMS: Random-forest classifier



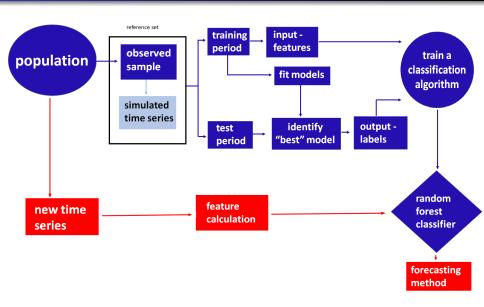
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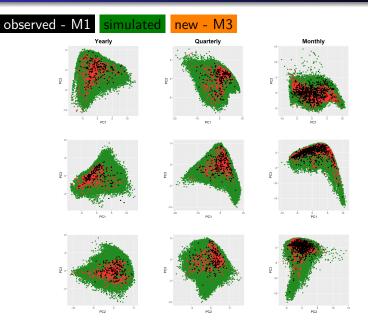


# Application to M competition data

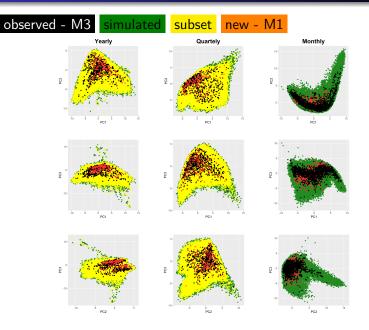
- Proposed algorithm is applied to yearly, quarterly and monthly series separately
- We run two experiments for each case.

	Experiment 1				Experiment 2			
	Source	Y	Q	M	Source	Y	Q	М
Observed series	M1	181	203	617	М3	645	756	1428
Simulated series		362000	406000	123400		1290000	1512000	285600
New series	М3	645	756	1428	M1	181	203	617

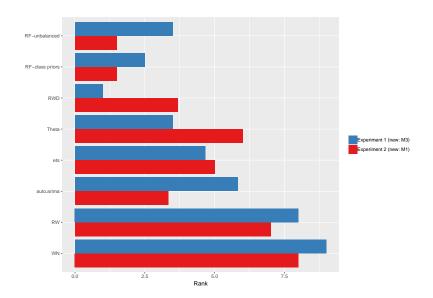
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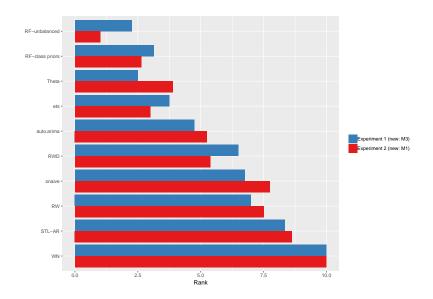
# Experiment 2: Distribution of time series in the PCA space



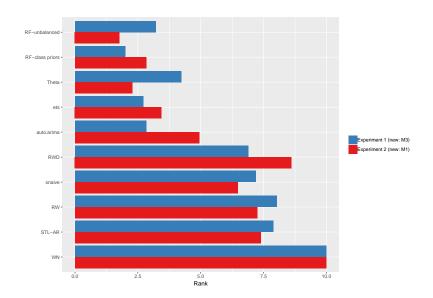
# Results: Yearly



# 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