# Meta-learning how to forecast time series

Thiyanga S Talagala
Rob J Hyndman
George Athanasopoulos

Monash University, Australia

International Symposium on Forecasting, 2018

# 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 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

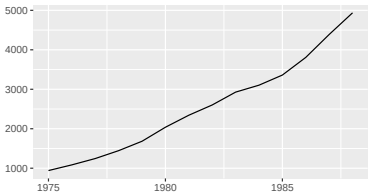
# Feature-space of time series

## STL-decomposition

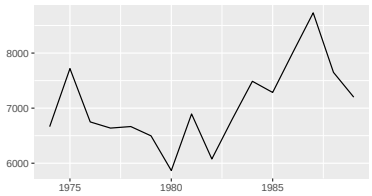
$$Y_t = T_t + S_t + R_t$$

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

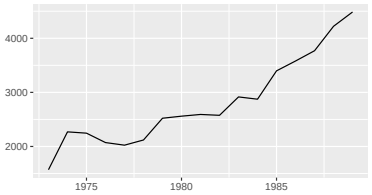
**N0001**



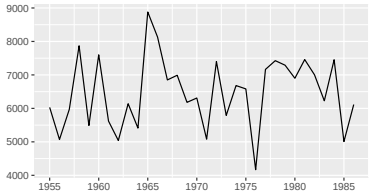

**N0633**



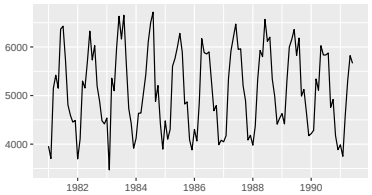

**N0625**



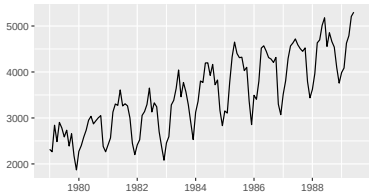

**N0645**




**N1912**




**N2012**

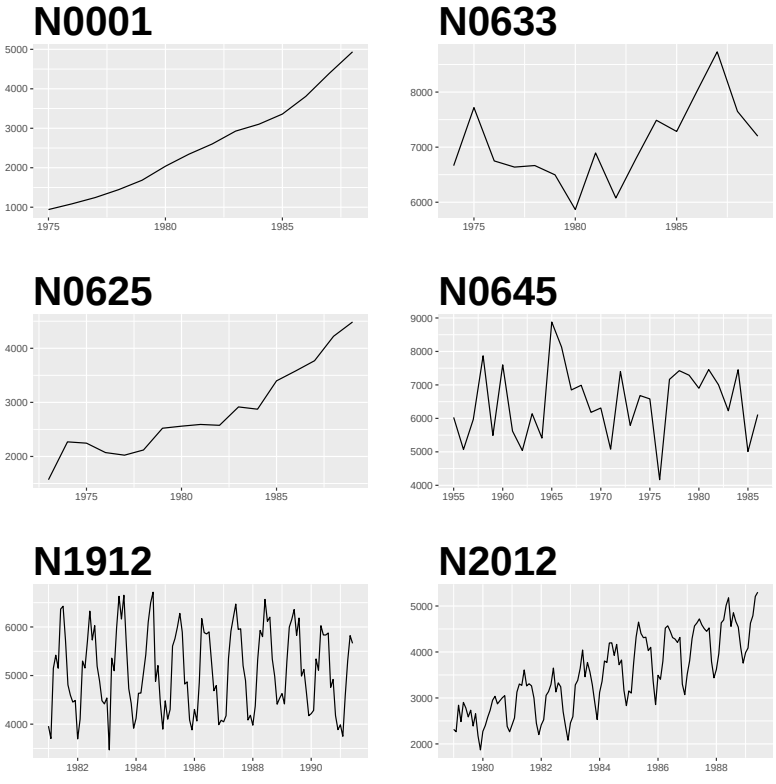


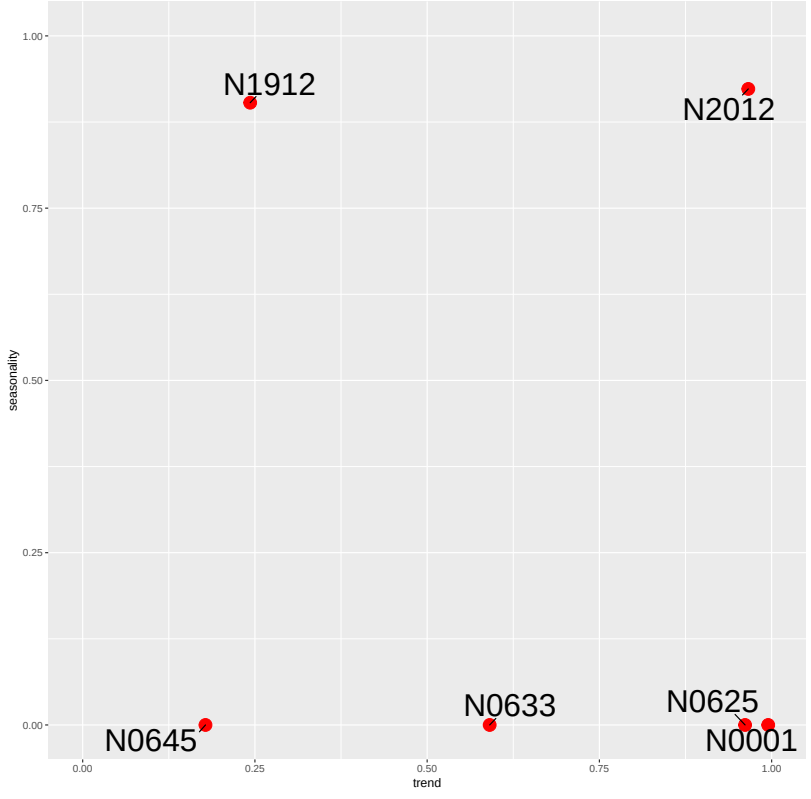
# Feature-space of time series

## 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: F**eature-based **FOR**ecast **M**odel **S**election

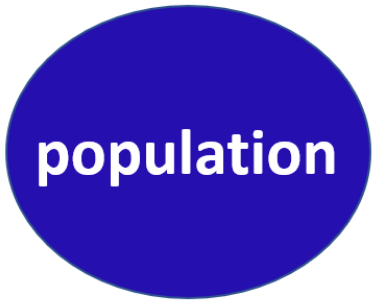
Offline

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

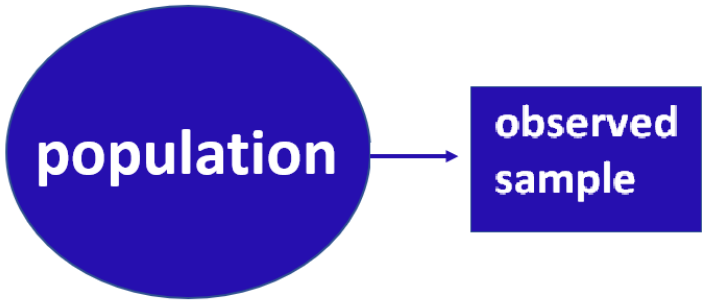
Online

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

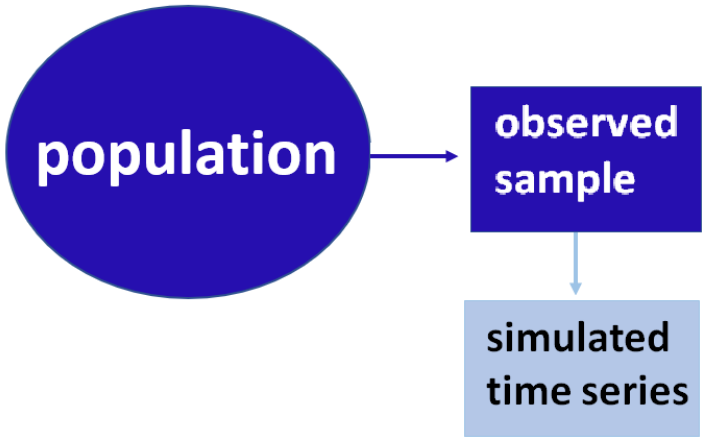
# FFORMS: population



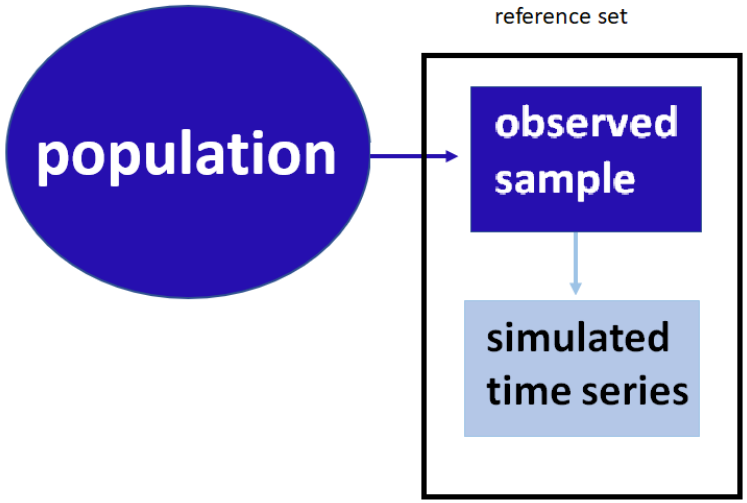
# FFORMS: observed sample



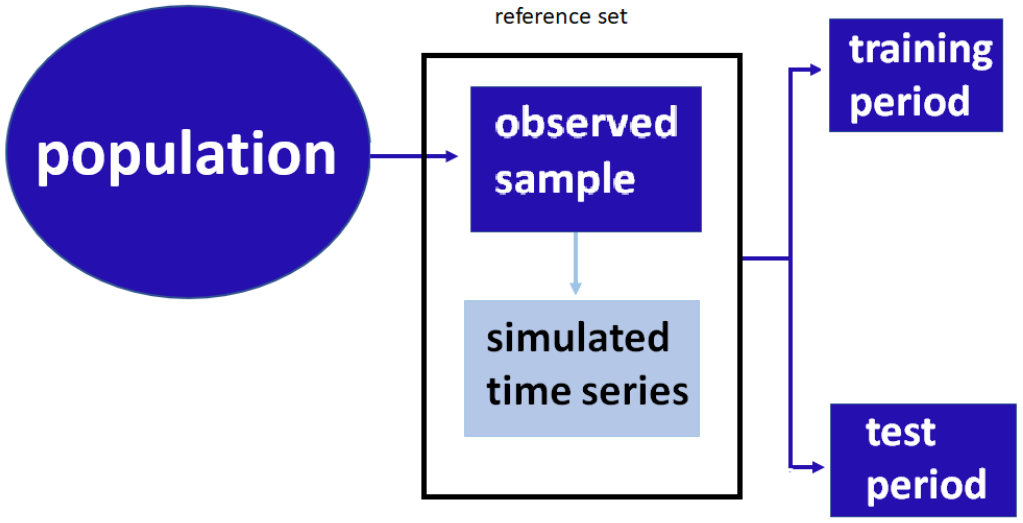
# FFORMS: simulated time series



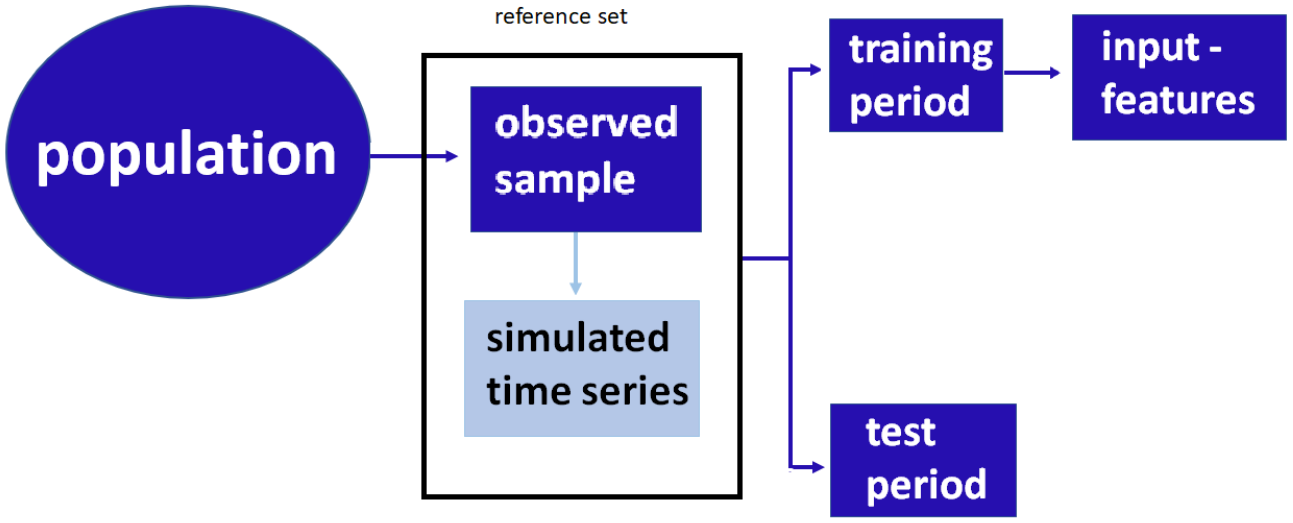
# FFORMS: reference set



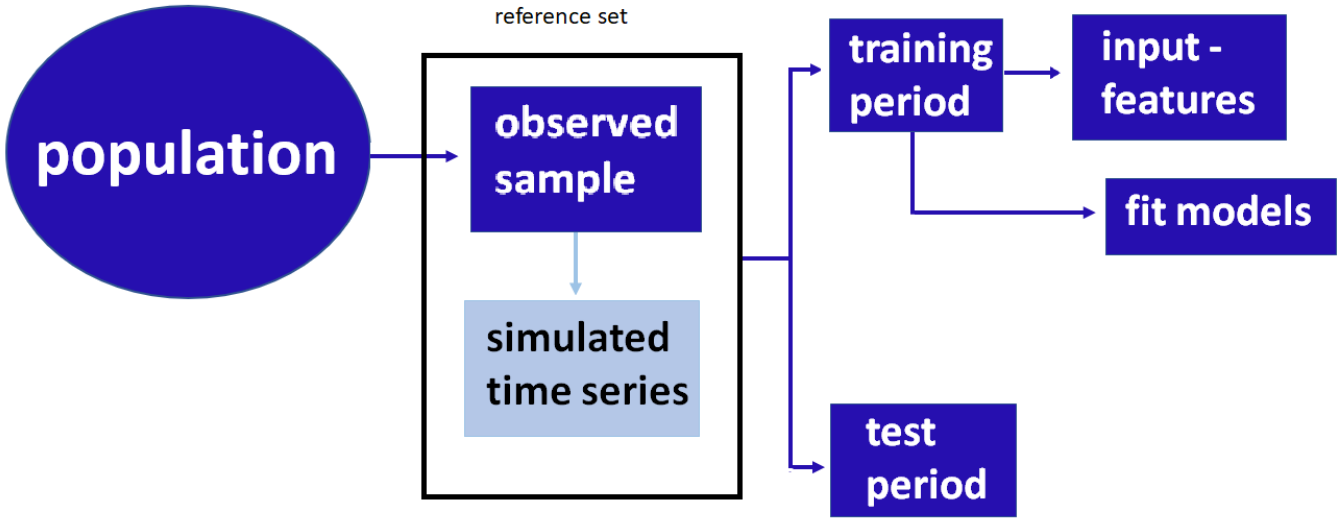
# FFORMS: Meta-data



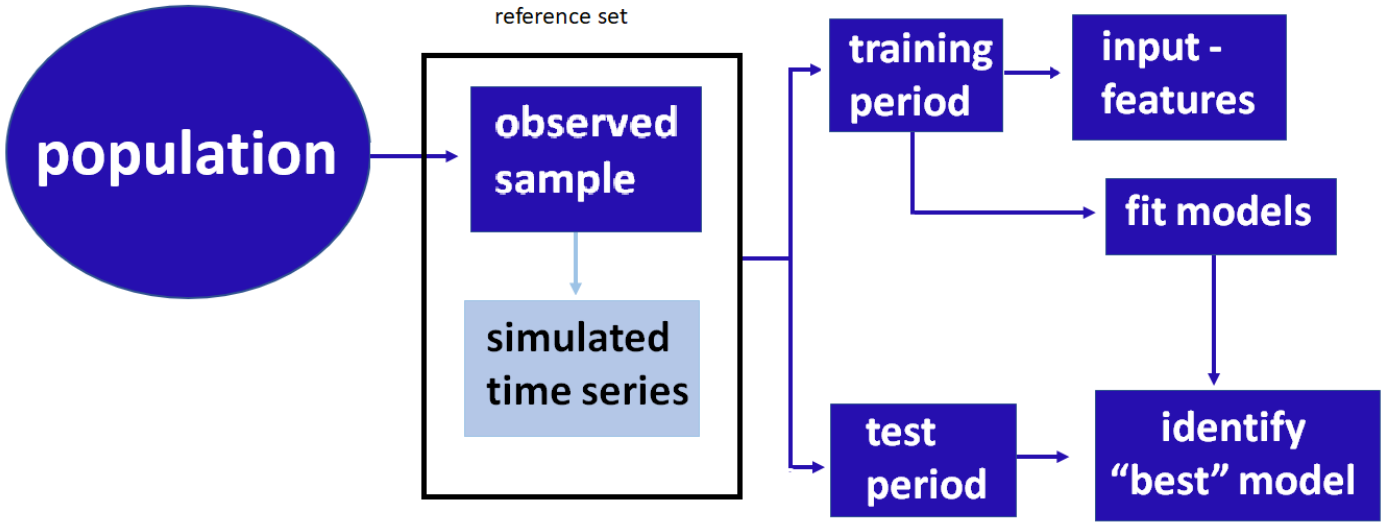
# FFORMS: Meta-data



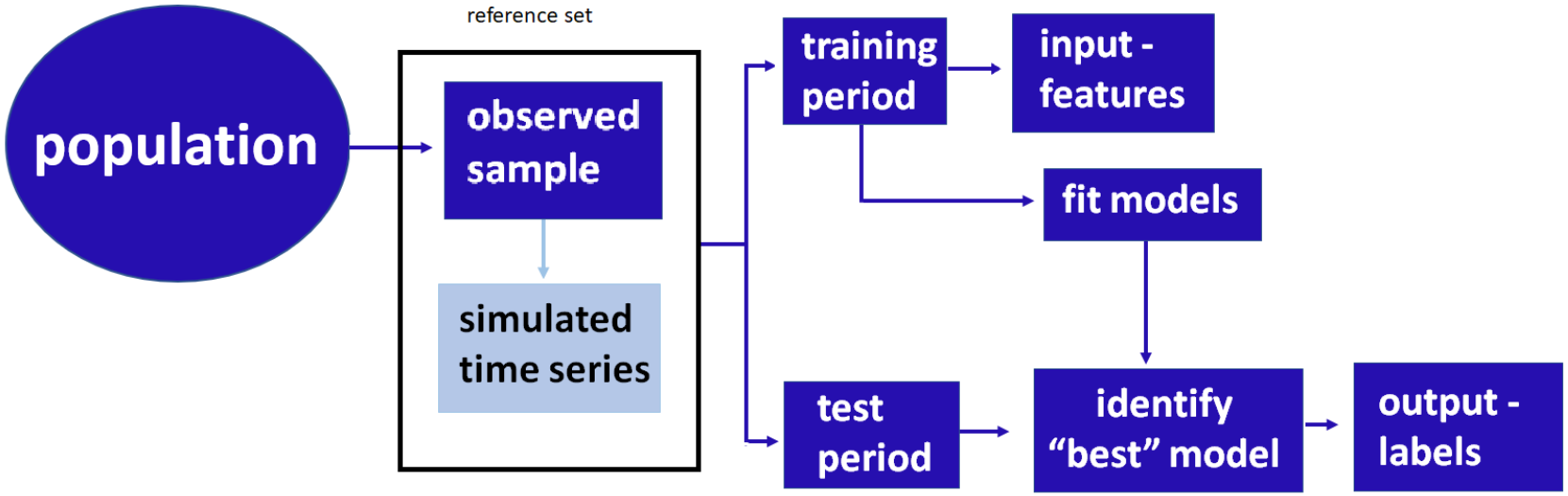
# FFORMS: Meta-data



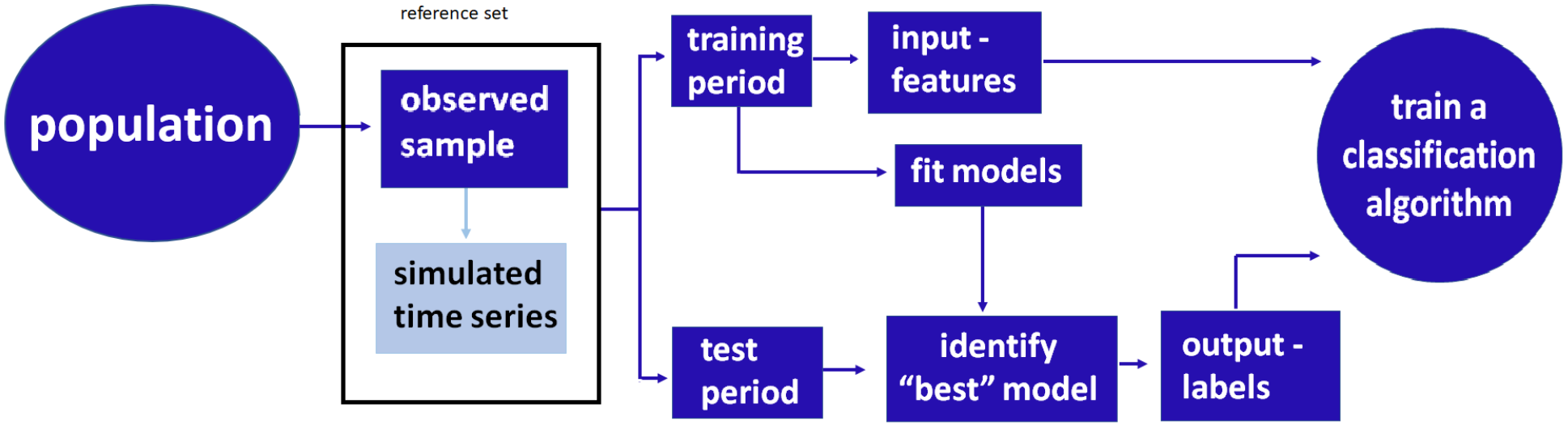
# FFORMS: Meta-data



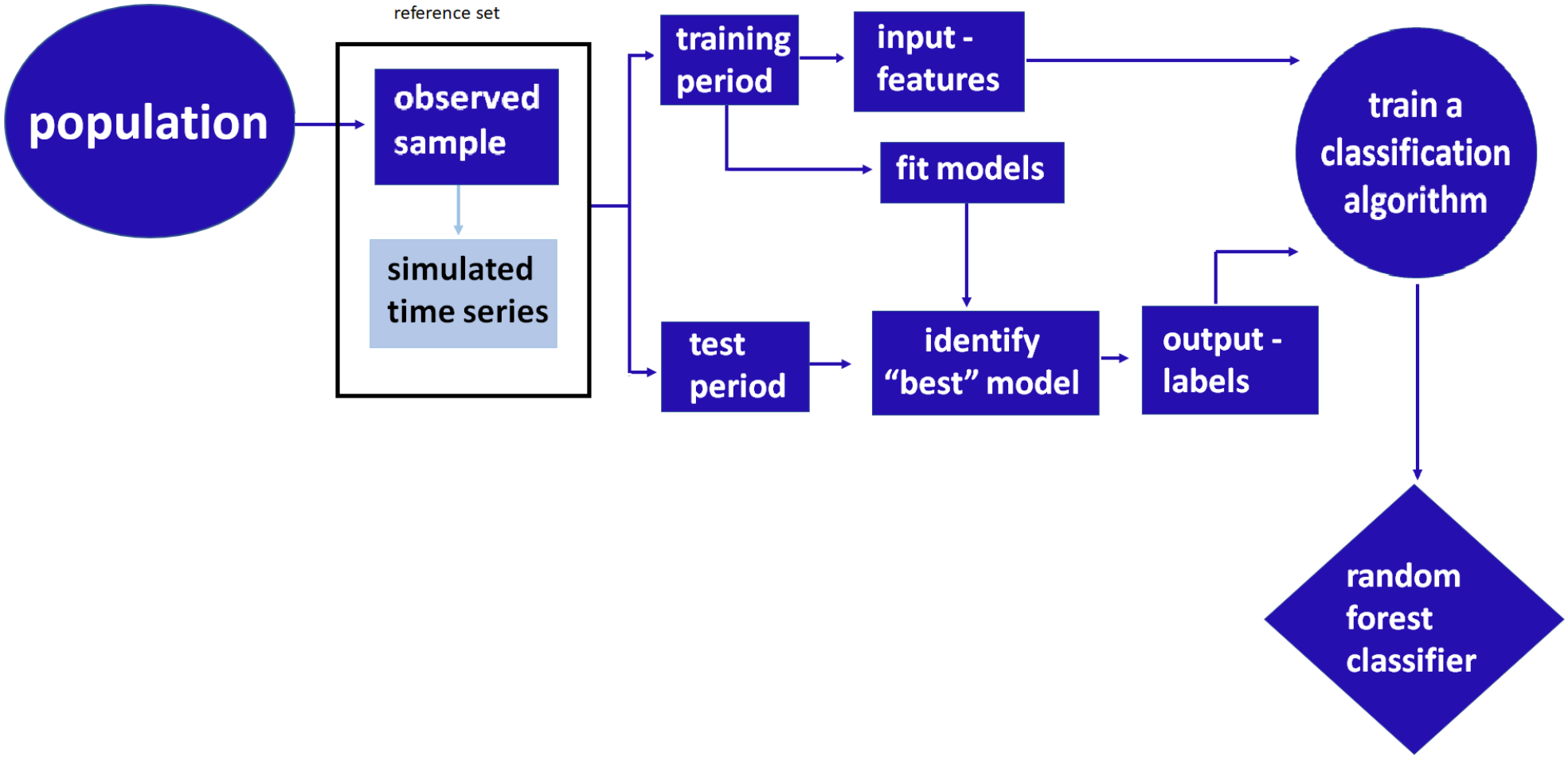
# FFORMS: Meta-data



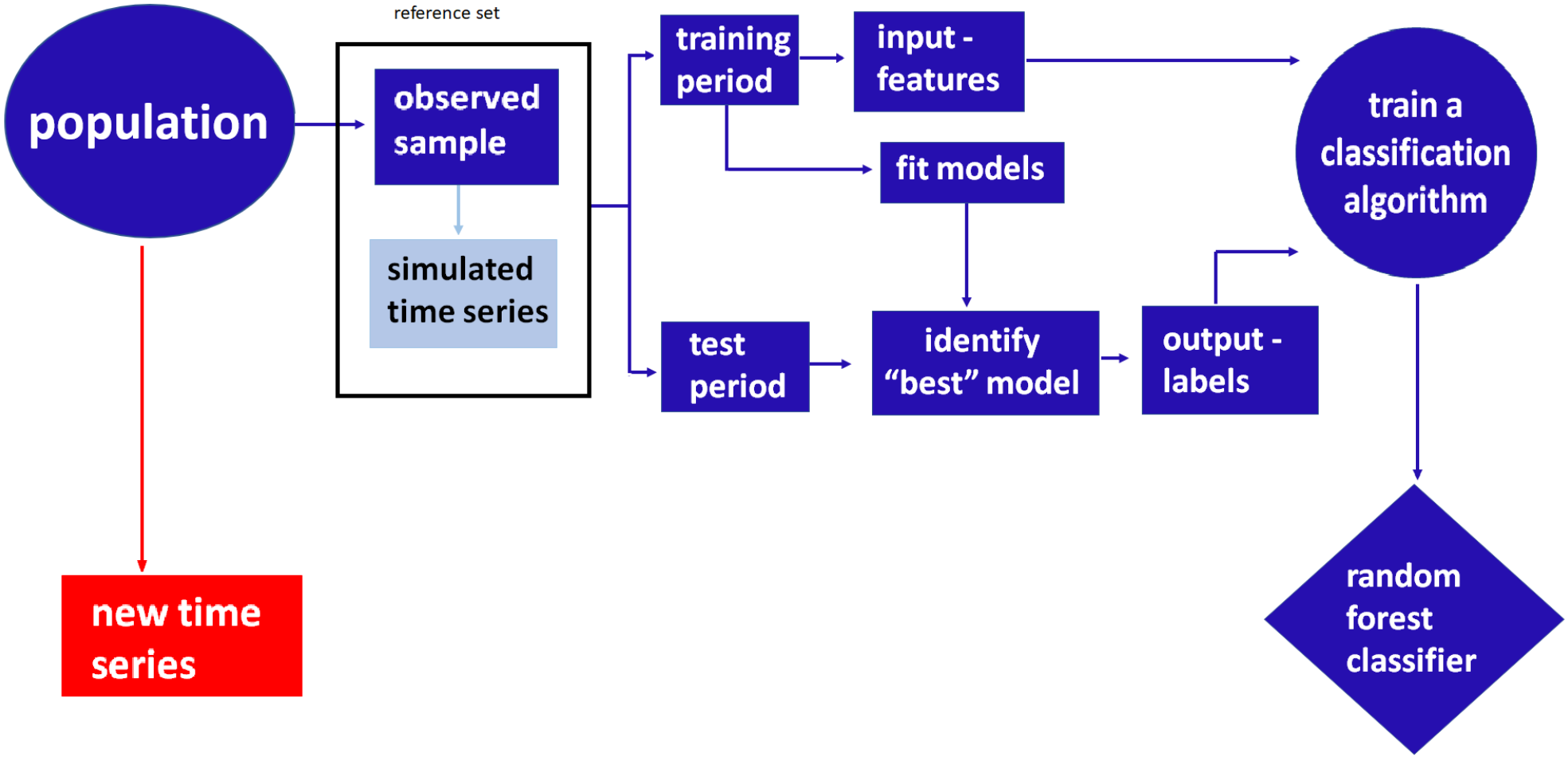
# FFORMS: Meta-data



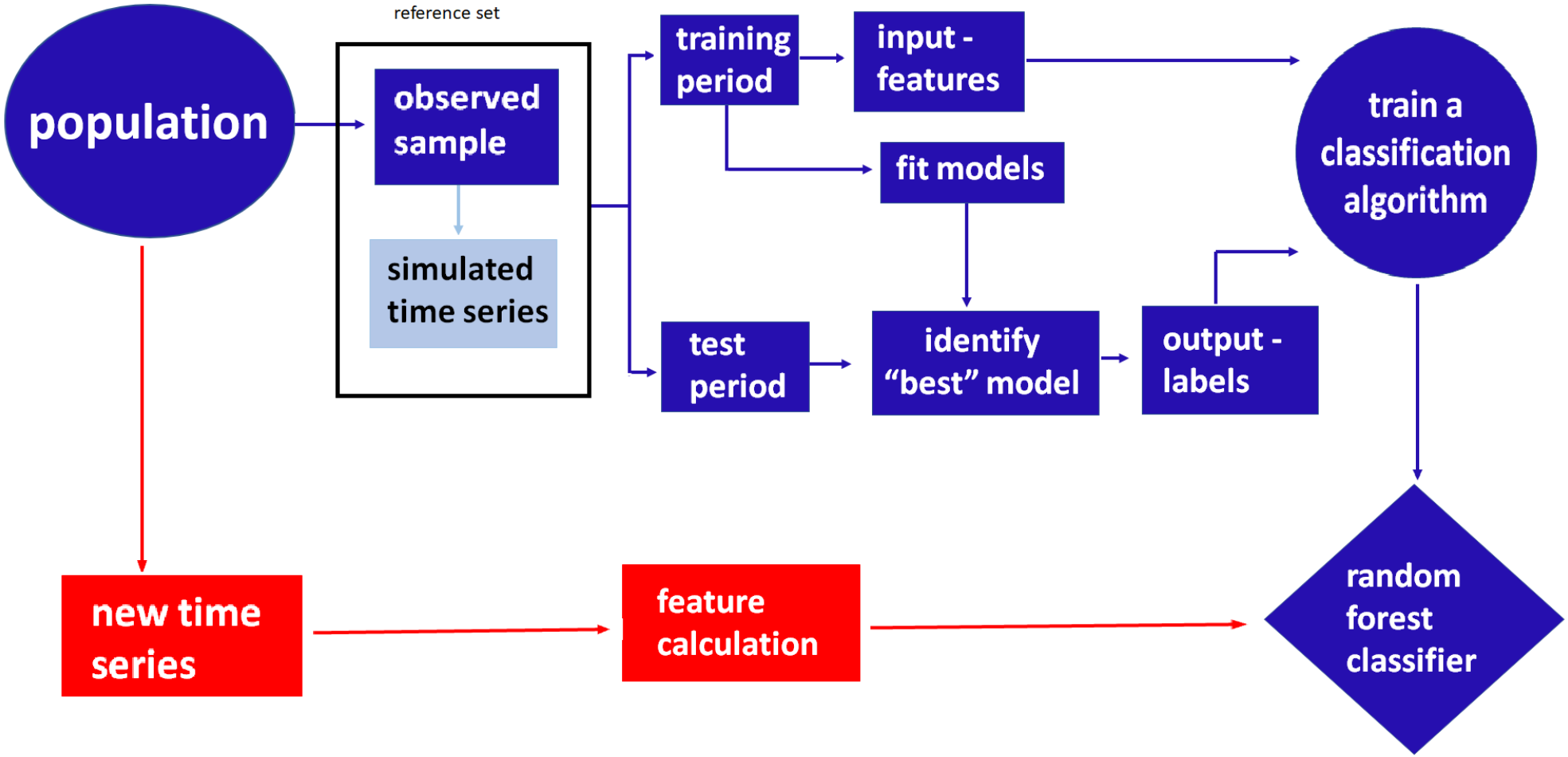
# FFORMS: Random-forest classifier



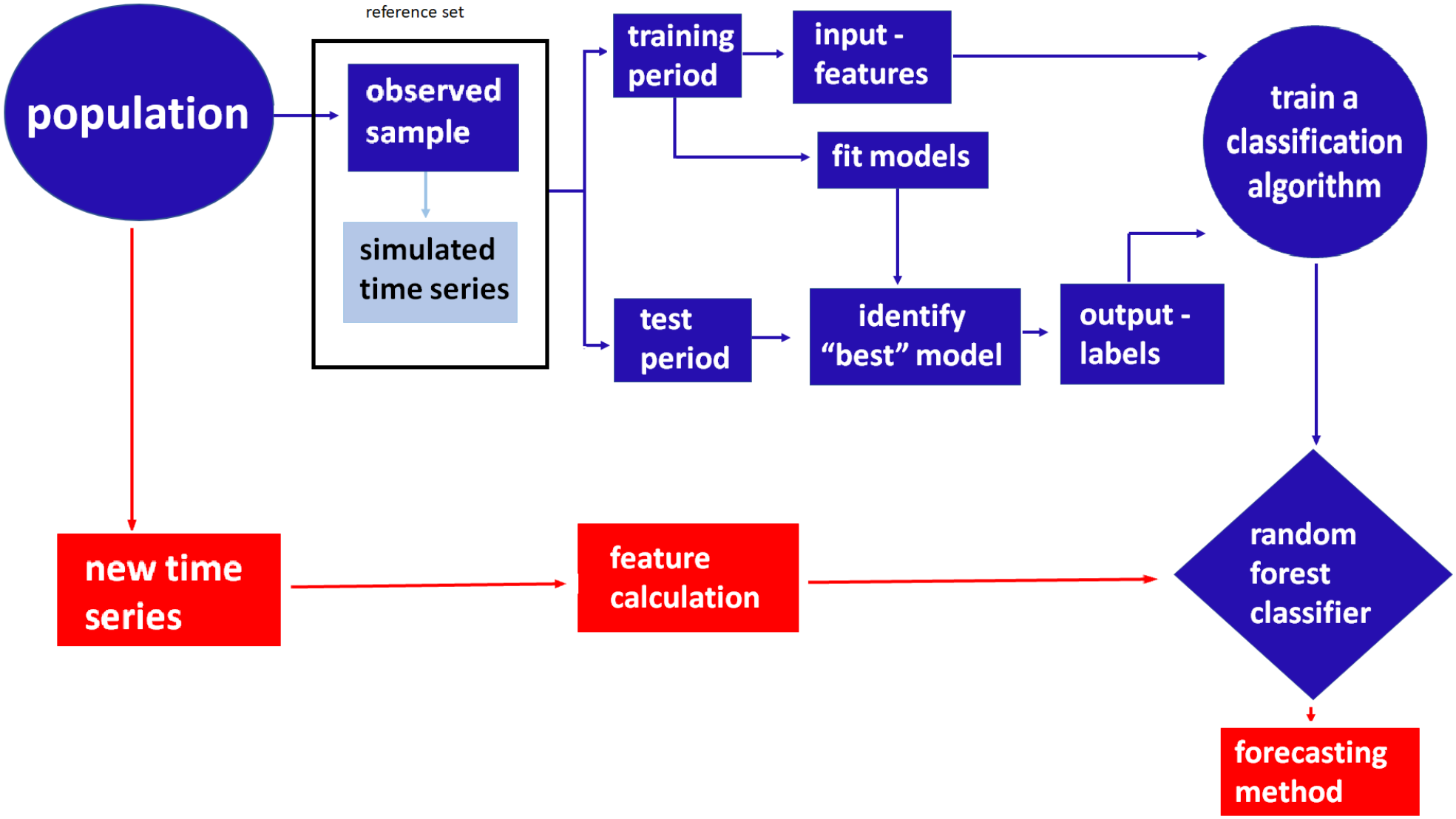
# FFORMS: "online" part of the algorithm



# FFORMS: "online" part of the algorithm



# FFORMS: "online" part of the algorithm



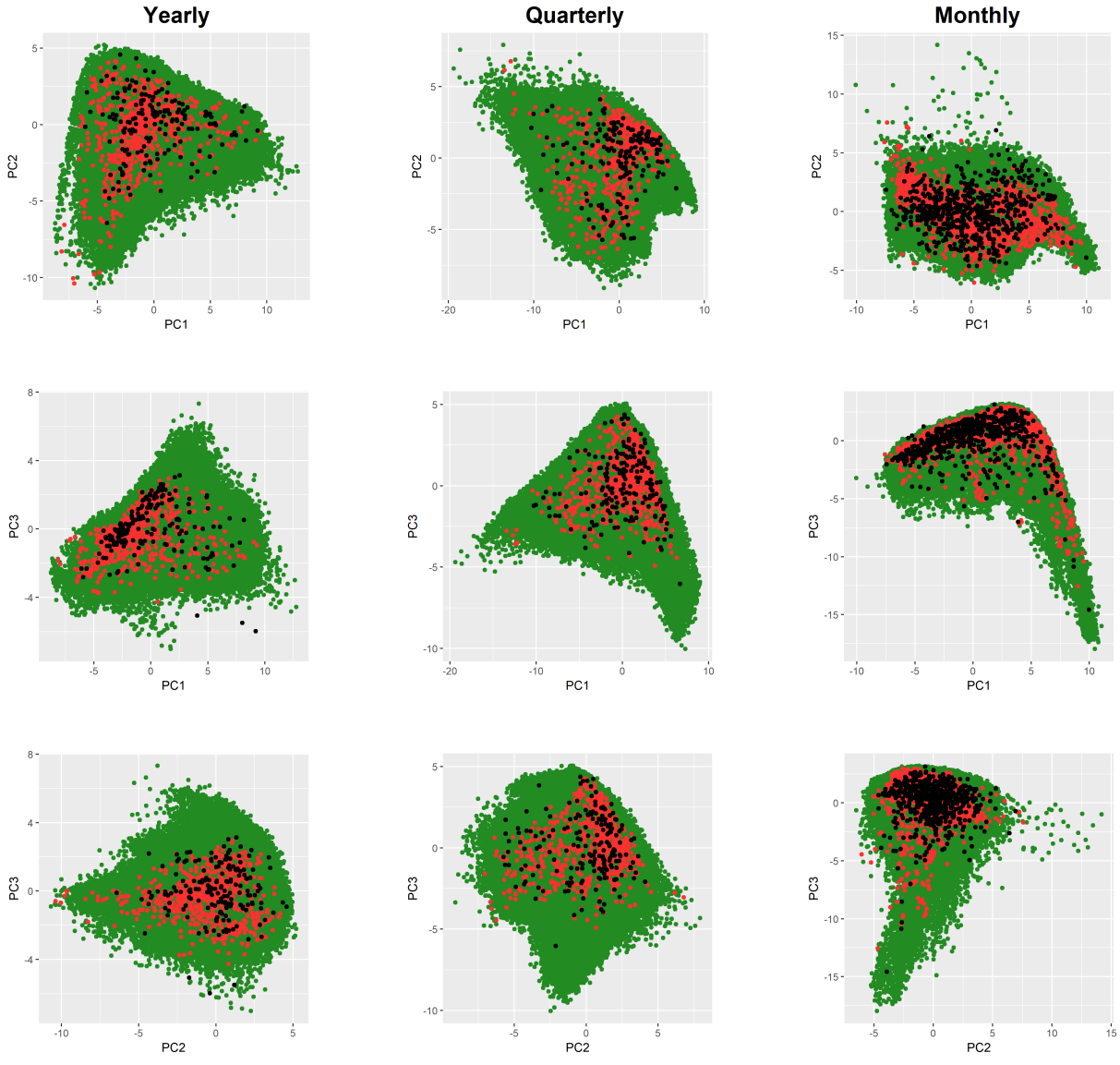
# Application to M competition data

- 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 |

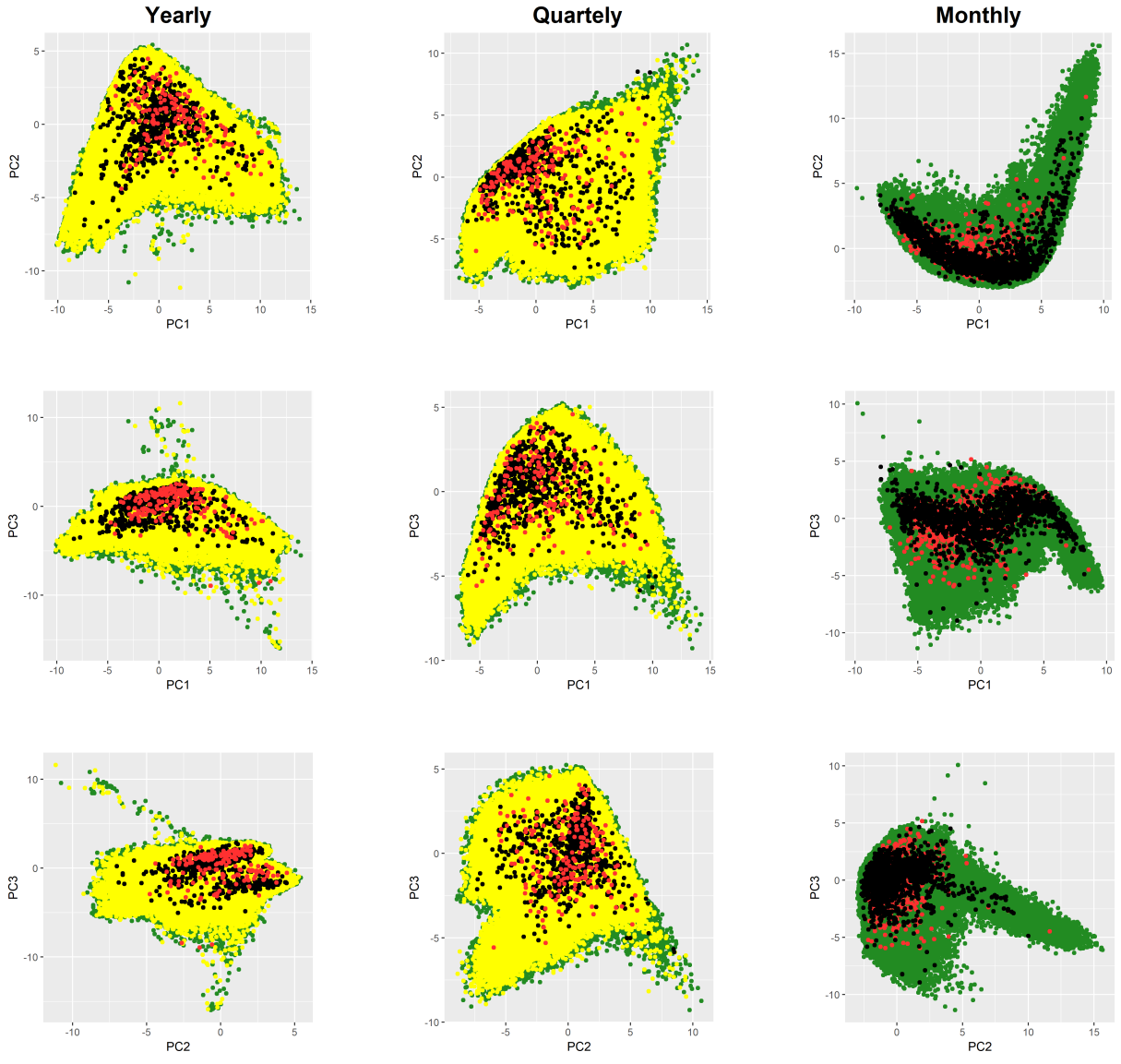
# Experiment 1: Distribution of time series in the PCA space

observed - M1 | simulated | new - M3

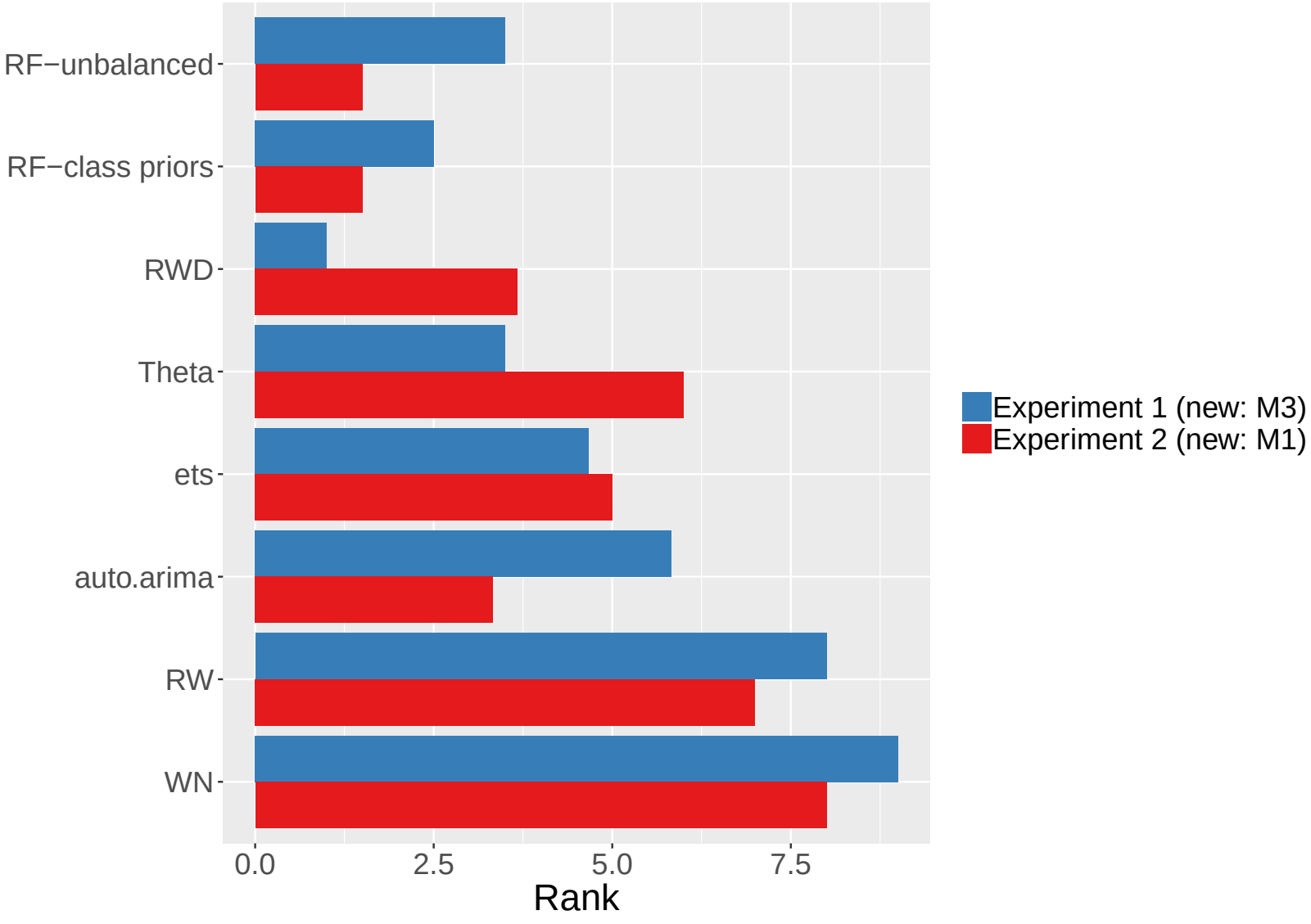


# Experiment 2: Distribution of time series in the PCA space

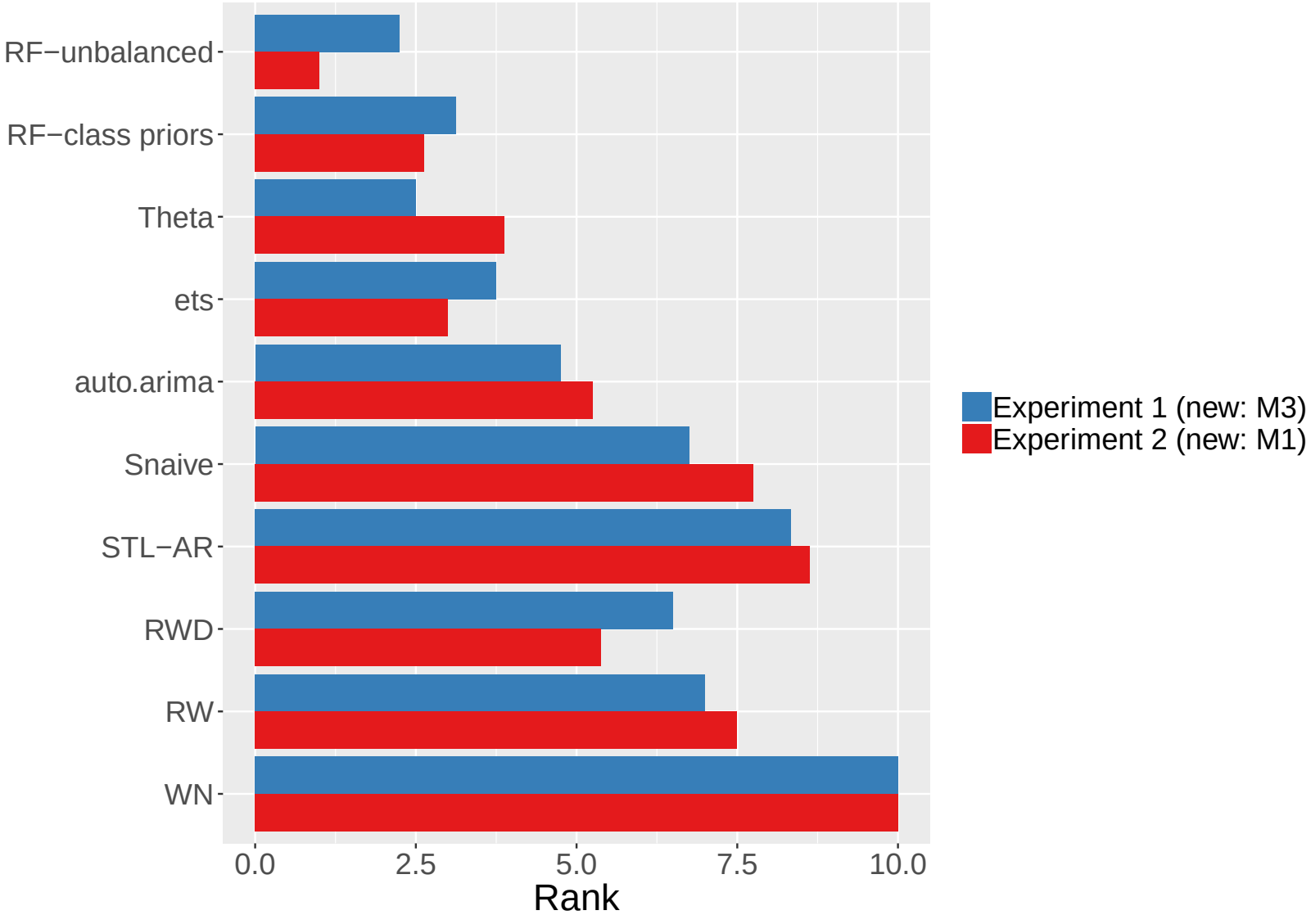
observed - M3 | simulated | subset | new - M1



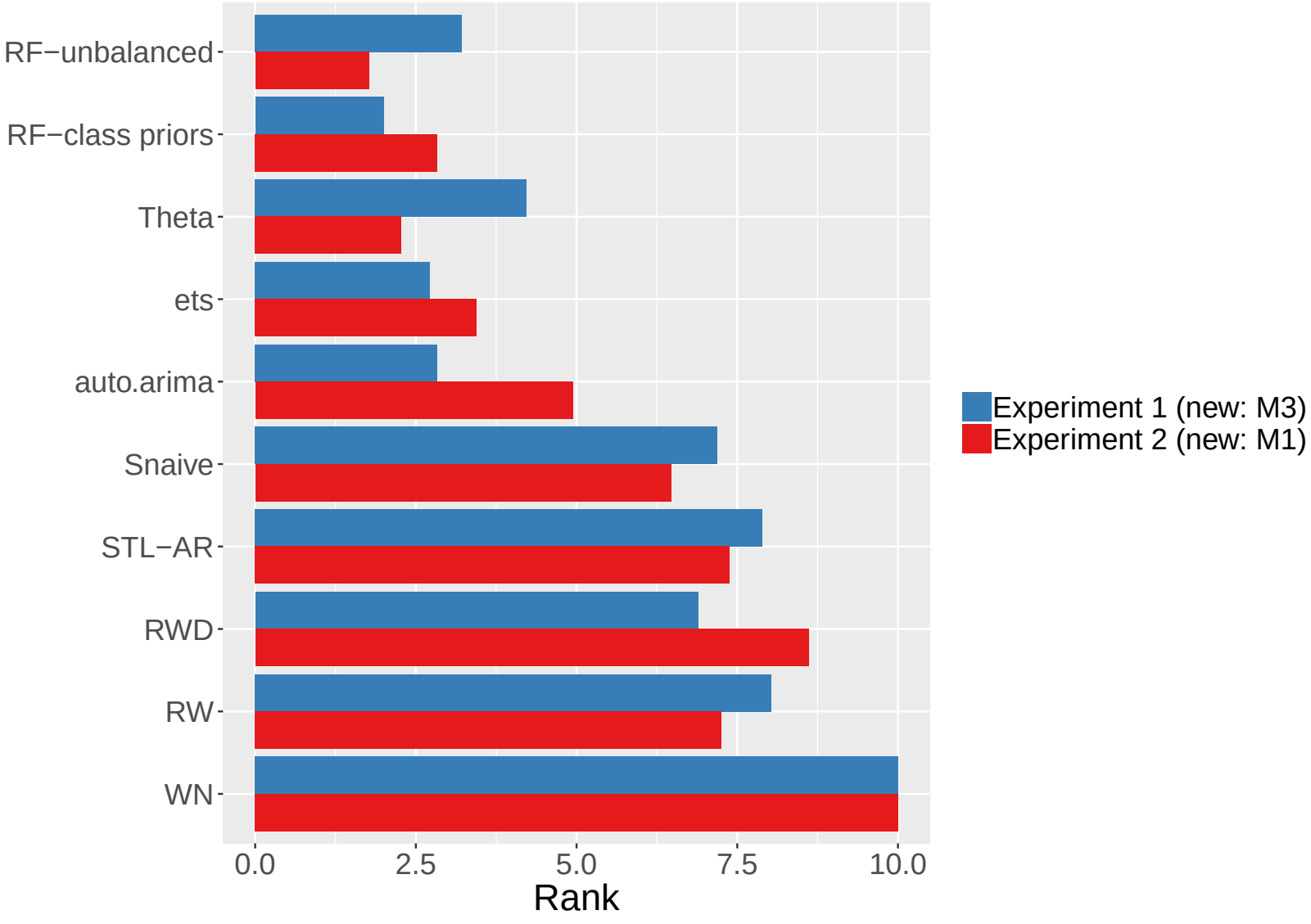
# Results: Yearly



# 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

```
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