

seer: R package for feature-based forecast model selection

Thiyanga S Talagala
Rob J Hyndman
George Athanasopoulos

Monash University, Australia

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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.

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

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

FFORMS: Feature-based FORecast Model Selection

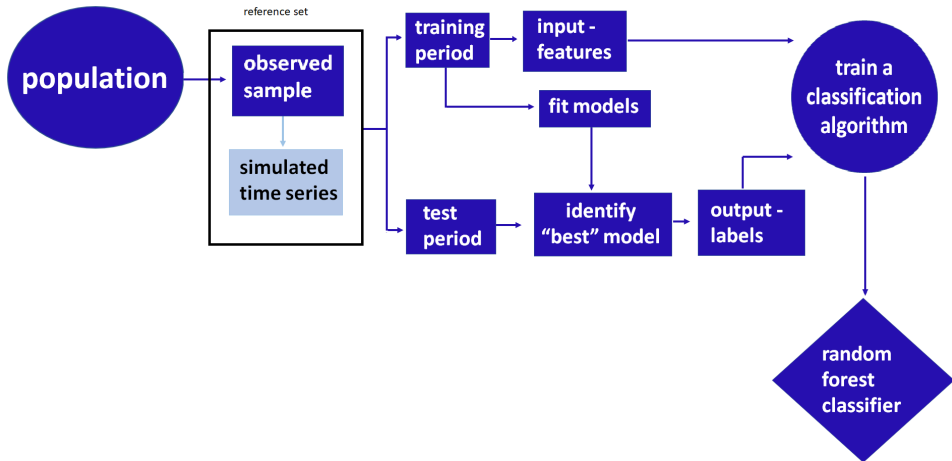
Offline

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

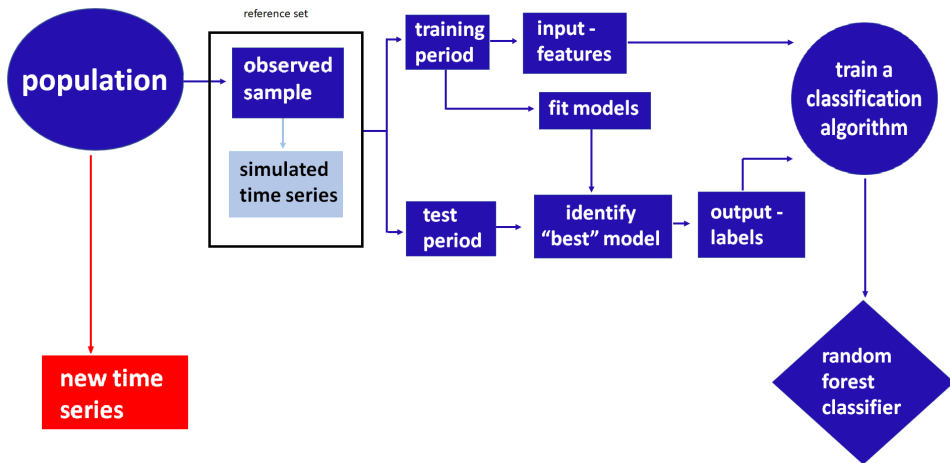
Online

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

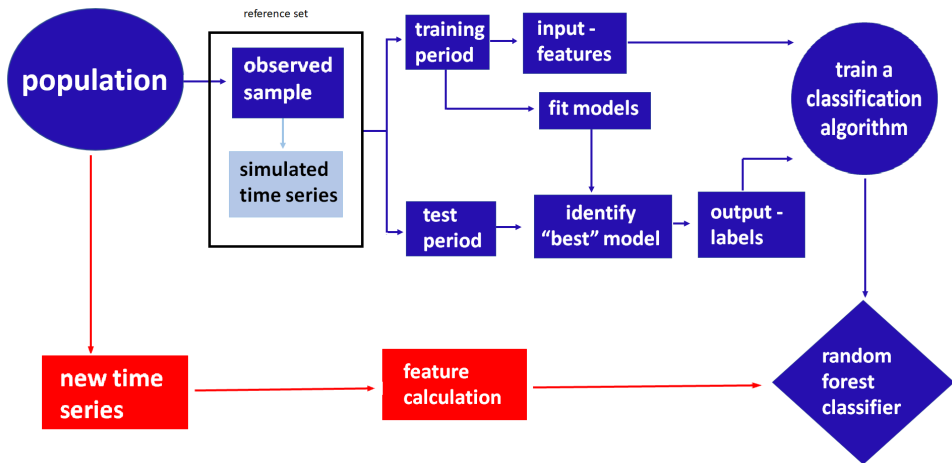
FFORMS: “offline” part of the algorithm



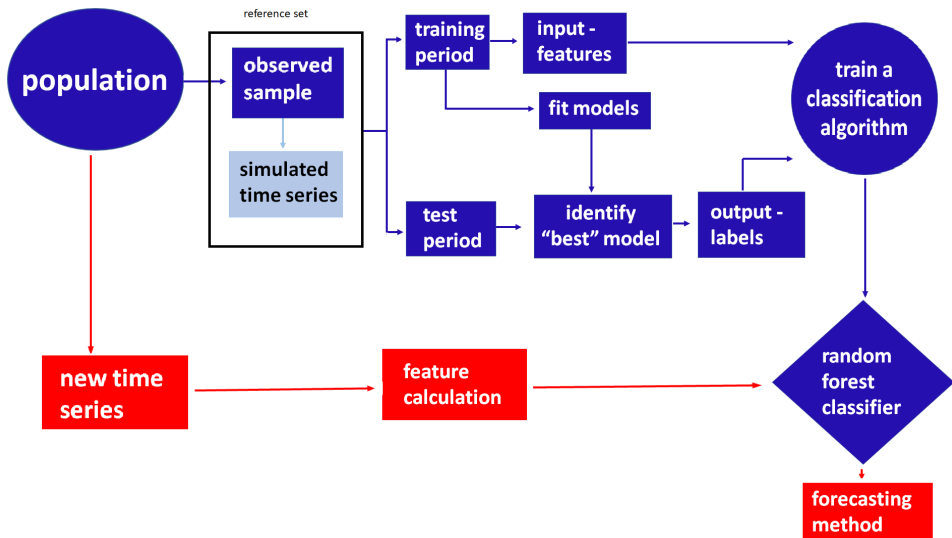
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Installation

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devtools::install_github("thiyanagt/seer")  
library(seer)
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Example data set:

```
library(Mcomp)  
yearly_m3 <- subset(M3, "yearly")  
yearly_m3
```

M-Competition data: 645 YEARLY time series

Type of data							
Period	DEMOGRAPHIC	FINANCE	INDUSTRY	MACRO	MICRO	OTHER	
YEARLY	245	58	102	83	146	11	

Input: features

	entropy	lumpiness	stability	hurst	trend	spike
1	0.7729350	0	0	0.9710509	0.9950394	5890
2	0.8374974	0	0	0.9473065	0.8687934	6020568
3	0.8250352	0	0	0.9486339	0.8648297	6689308
	curvature	e_acf1	y_acf1	diff1y_acf1	diff2y_acf1	
1	531.9694	0.4124236	0.7623182	0.5974236	-0.004813322	0
2	-2823.8839	0.3240316	0.7507872	0.2399691	-0.398246929	0
3	-3078.0284	0.4571183	0.7687310	0.4461251	-0.211798893	0
	diff1y_pacf5	diff2y_pacf5	nonlinearity	lmres_acf1	ur	
1	0.5483426	0.2301945	2.124405	0.4819001	1.3292	
2	0.1565805	0.3074159	1.998710	0.7227836	-3.7353	
3	0.3708305	0.1717048	1.449664	0.7645834	-3.9785	
	y_acf5	diff1y_acf5	diff2y_acf5	alpha	beta	
1	1.0230152	0.4213774	0.3614128	0.9998869	0.9998869	
2	0.9855601	0.1338517	0.5582498	0.9998999	0.2171013	
3	1.0798980	0.3609988	0.7632291	0.9998999	0.5054122	

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

Discussion and Conclusions

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- 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.

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- 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.



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

Email: thiyanga.talagala@monash.edu