MONASH University

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Feature-based Model Selection for Time Series Forecasting

Thiyanga Talagala

Rob J Hyndman

George Athanasopoulos

Large collections of time series

Freelance **Forecasting Multiple time series** 8 Mar 2016

Logistics Capital & Strategy – Posted by LogCapStrat – **Anywhere**

Logistics CAPITAL & STRATEGY

Job Description

Logistics Capital & Strategy is looking for a Data Scientist with expertise in Parallel computing to assist in code optimization and parallel processing of an under development forecasting model in R.

This is a contract position and we are expecting the project to completed over a period of 2 weeks.

Skills Required:
R Programming/Python/Scala (for code development)
MSSQL for data extraction into programming environment
Apache Spark or related big data processing frameworks to allow for high speed data processing

Project Scope:
The current forecasting model build on R needs to be scaled, and optimized to allow forecasting of millions of individual time series, ideally in a span of few hours.

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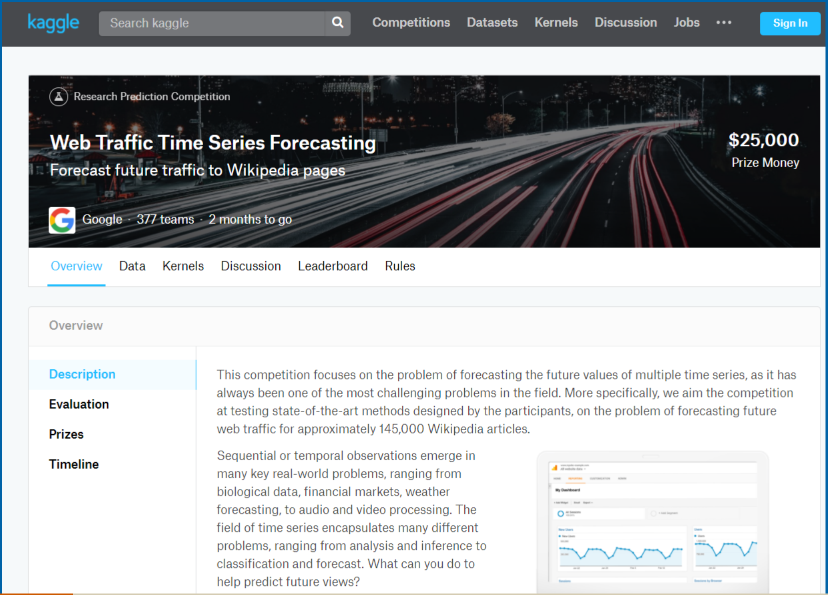

Large collections of time series

Forecasting multiple time series

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  - Develop a single method which provides better forecasts across all time series.

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- Individual model building or combined forecasts

Automatic time series forecasting

- ets algorithm
- auto.arima algorithm

ets() and auto.arima() in R

ets algorithm

- Apply each of 15 ETS models that are appropriate to the data

auto.arima algorithm

- Use stepwise search to traverse model space, starting with a simple model

- For each model, optimize parameters using MLE
- Select best method using AICc

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Motivation

Reid(1972) pointed out that the performance of various forecasting methods changes according to the nature of data and if the reasons for these variations are explored they may be useful in selecting the most appropriate model.

Objective

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

Time series features

Cognostics: Computer-aided diagnostics
(John W. Tukey, 1985)

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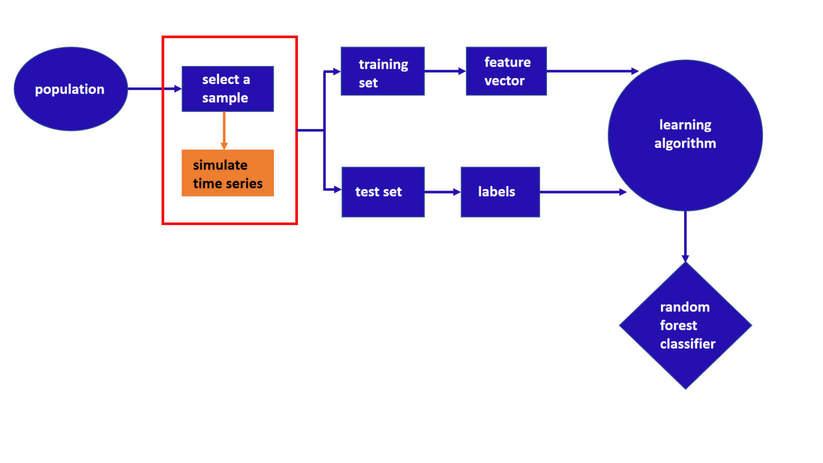
  - strength of seasonality
  - lag correlation
  - spectral entropy

Methodology: “offline” part of the algorithm



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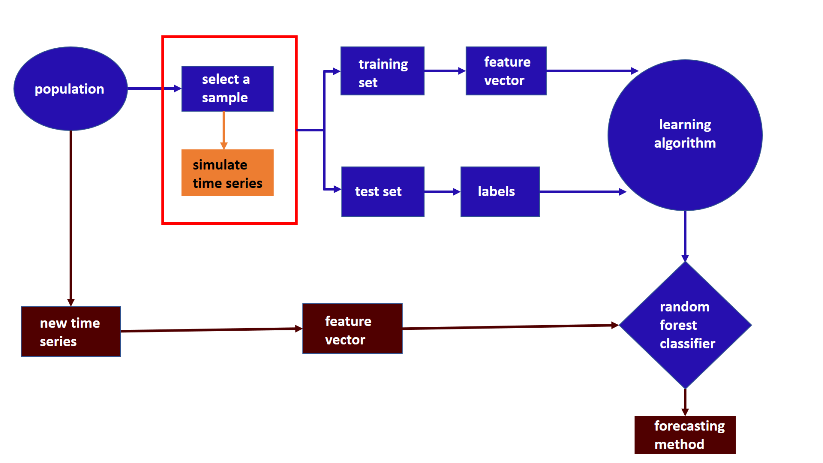
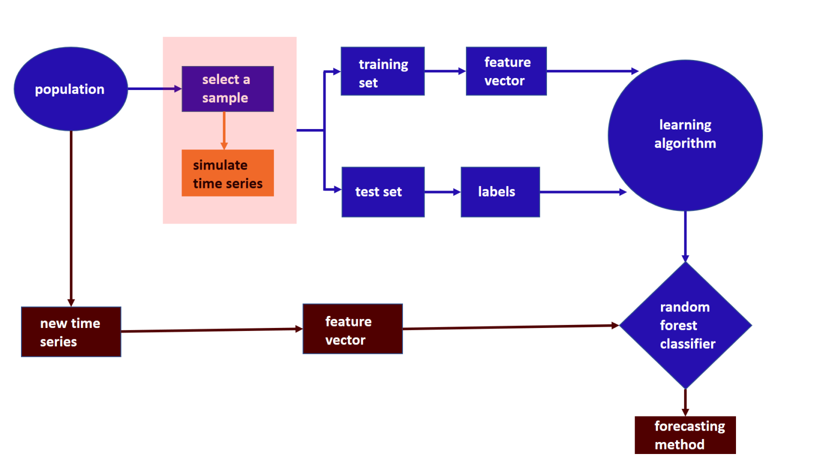
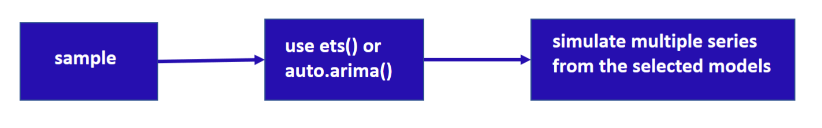


Methodology: reference set

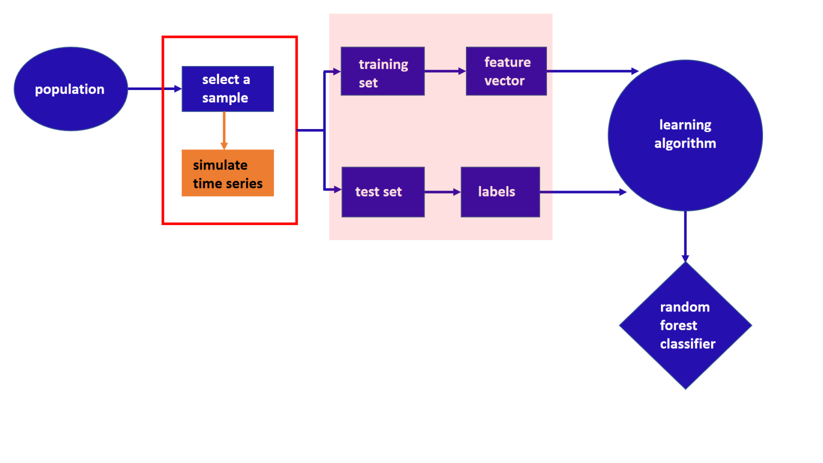


Augmenting the reference set with simulated series

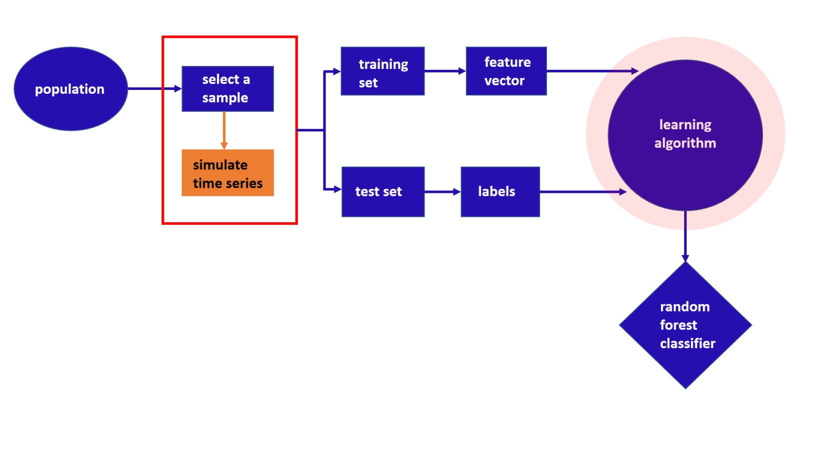
- when our sample is too small to build a reliable classifier
- when we wish to add more of some types of time series to the training set in order to get a more balanced sample
- How?



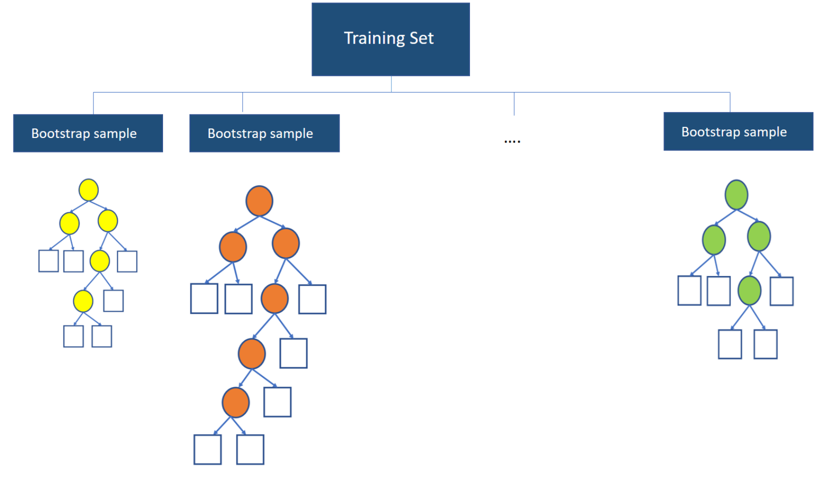
Methodology: features and class labels



Methodology: random forest



Random forest



The random forest algorithm for classification

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- Overall prediction: Majority vote from all individually built trees.

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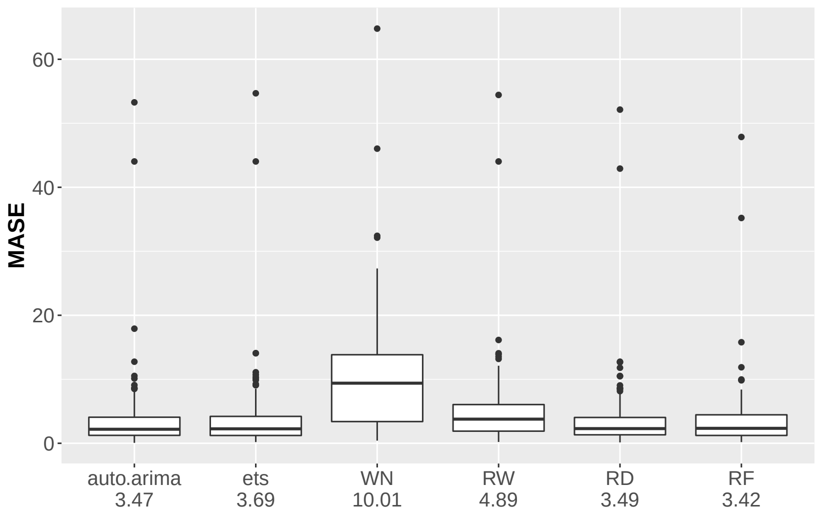
- Data: Yearly time series of M1 and M3 competitions
  - Classification algorithm - yearly series of M3 competition
  - Evaluation - yearly series of M1 competition
- Class labels
  - We consider random walks, white noise, ARIMA processes and ETS processes
  - The model with the smallest MASE

Time series feature

- Strength of trend
- Spectral entropy
- Hurst exponent
- Lyapunov exponent
- Parameter estimates of Holt linear trend model
- Length
- Coefficient of determination of the linear trend model
- ACF and PACF based features - calculated on both the raw and differenced series

Results: Distribution of MASE



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- Develop a more comprehensive set of features that are useful in identifying different data generating processes.
- Extend the time series collection to non-seasonal data.
- Test for several large scale real time series data sets.
- Consider other classification methods.

Acknowledgement

The Victorian Branch of the Statistical Society of Australia Inc. (SSA Vic)

Slides shared online at:

`https://github.com/thiyangt/YSC-2017`

`thiyanga.talagala@monash.edu`