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Feature-based Model Selection for Time Series Forecasting

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Large collections of time series

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

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

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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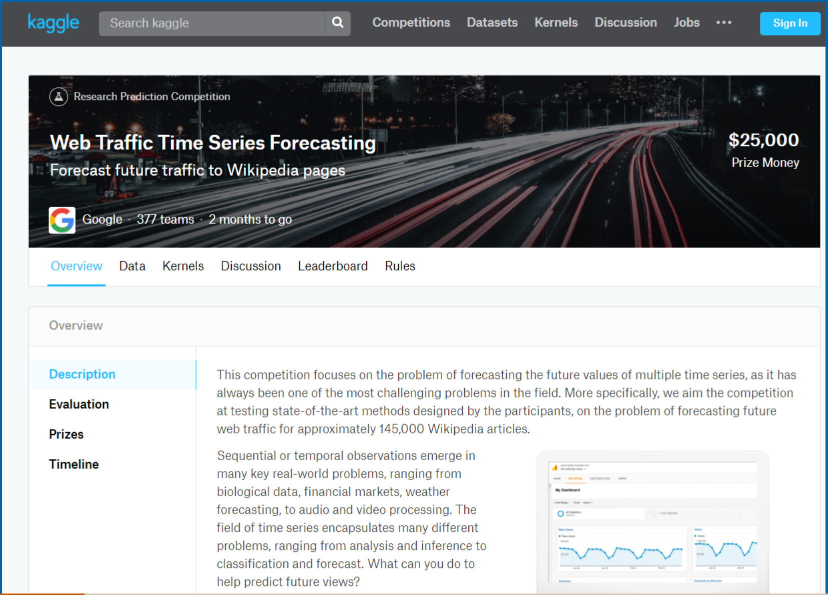

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  - Develop a single method which provides better forecasts across all time series.

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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 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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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)

- Characteristics of time series

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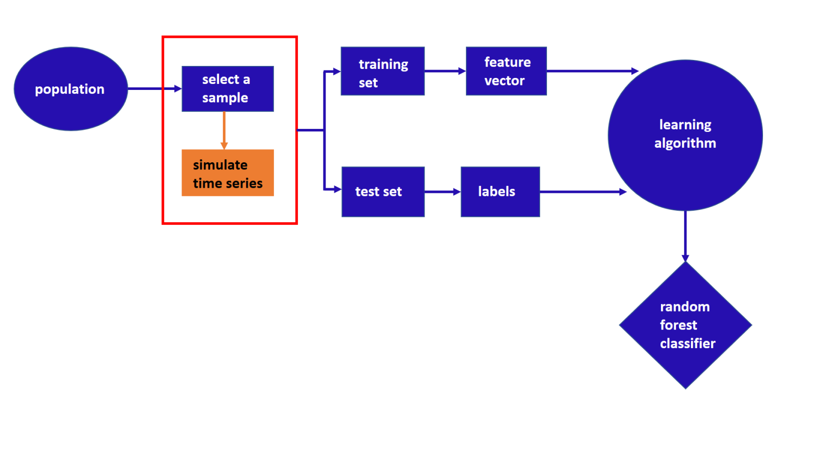
  - strength of seasonality
  - lag correlation
  - spectral entropy

Methodology: “offline” part of the algorithm



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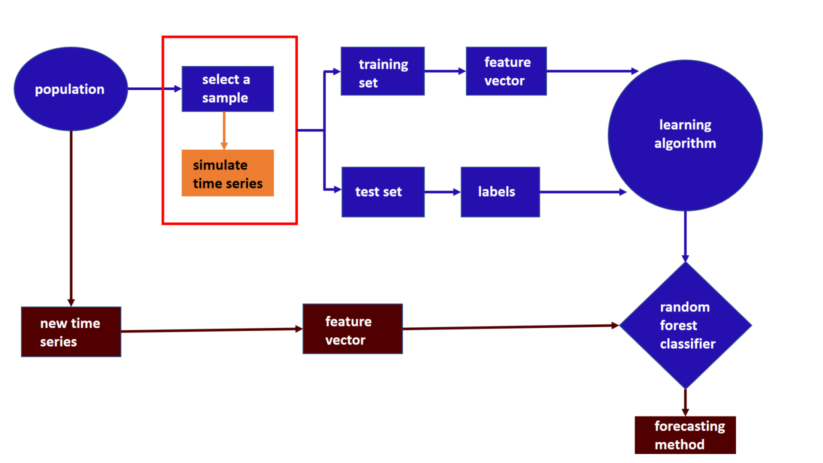
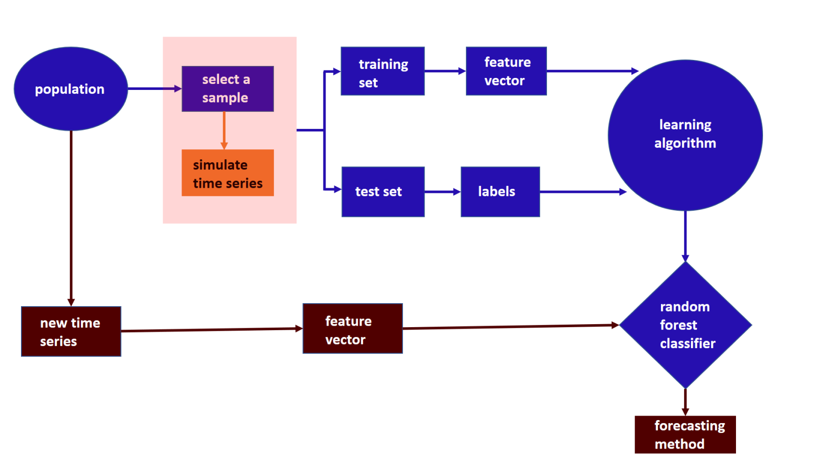
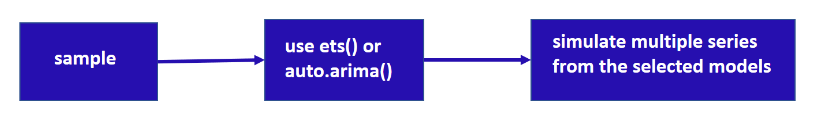


Methodology: reference set

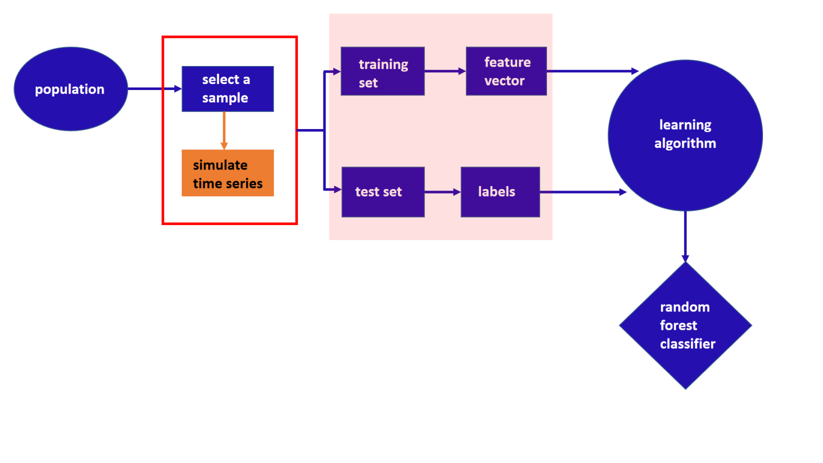


Augmenting the reference set with simulated series

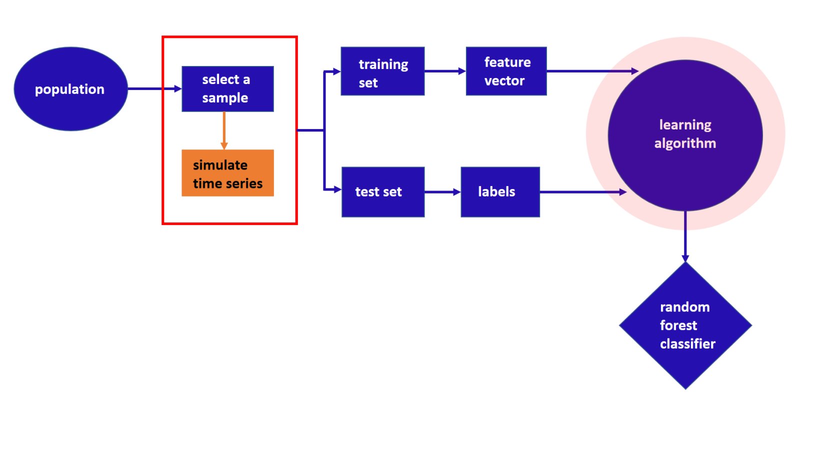
- when our sample is too small to build a reliable classifier
- when we wish to add more of some types of time series to the training set in order to get a more balanced sample
- How?



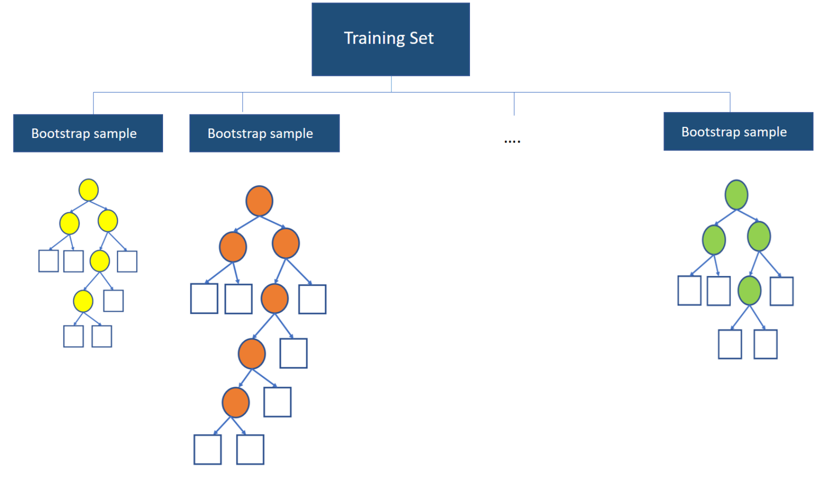
Methodology: features and class labels



Methodology: random forest



Random forest



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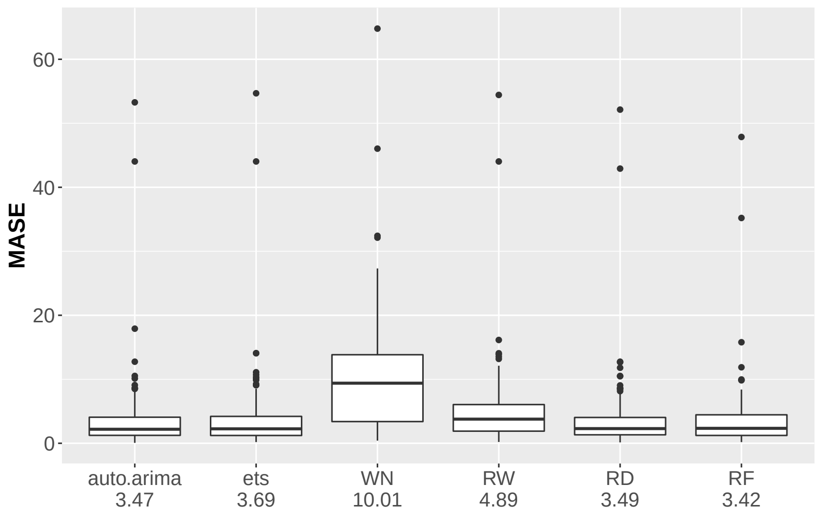
  - Classification algorithm - yearly series of M3 competition
  - Evaluation - yearly series of M1 competition
- Class labels
  - We consider random walks, white noise, ARIMA processes and ETS processes
  - The model with the smallest MASE

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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- Test for several large scale real time series data sets.

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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`