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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

Logistics Capital & Strategy – Posted by LogCapStrat –  Anywhere

2016



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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How to Apply

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Research Prediction Competition

Web Traffic Time Series Forecasting

Forecast future traffic to Wikipedia pages

\$25,000

Prize Money



Google · 377 teams · 2 months to go

[Overview](#)

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Overview

Description

Evaluation

Prizes

Timeline

This competition focuses on the problem of forecasting the future values of multiple time series, as it has always been one of the most challenging problems in the field. More specifically, we aim the competition at testing state-of-the-art methods designed by the participants, on the problem of forecasting future web traffic for approximately 145,000 Wikipedia articles.

Sequential or temporal observations emerge in many key real-world problems, ranging from biological data, financial markets, weather forecasting, to audio and video processing. The field of time series encapsulates many different problems, ranging from analysis and inference to classification and forecast. What can you do to help predict future views?

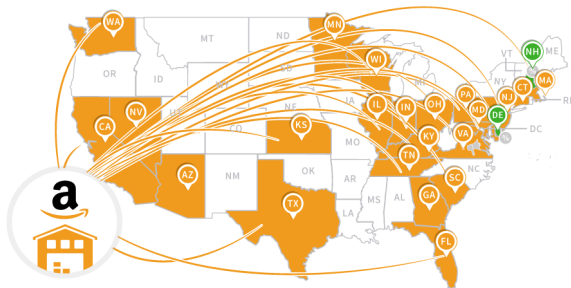


Large collections of time series



Amazon's Warehouse States

The states on this map have warehouses that store and ship inventory for Amazon FBA Sellers.



Forecasting multiple time series

- Aggregate selection rule

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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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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.

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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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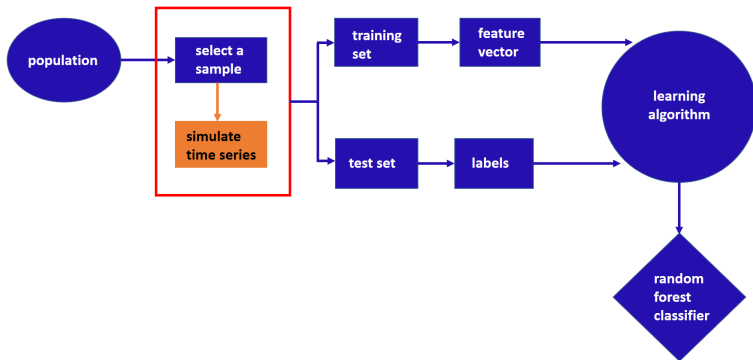
Time series features

Cognostics: Computer-aided diagnostics

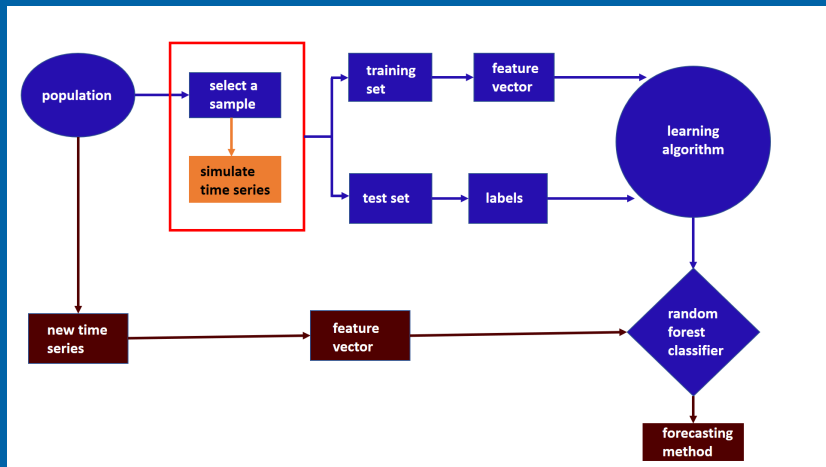
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- Characteristics of time series
- Depending on the research goals and domains, a variety of features have been introduced
- Examples for time series features
 - ▶ strength of trend
 - ▶ strength of seasonality
 - ▶ lag correlation
 - ▶ spectral entropy

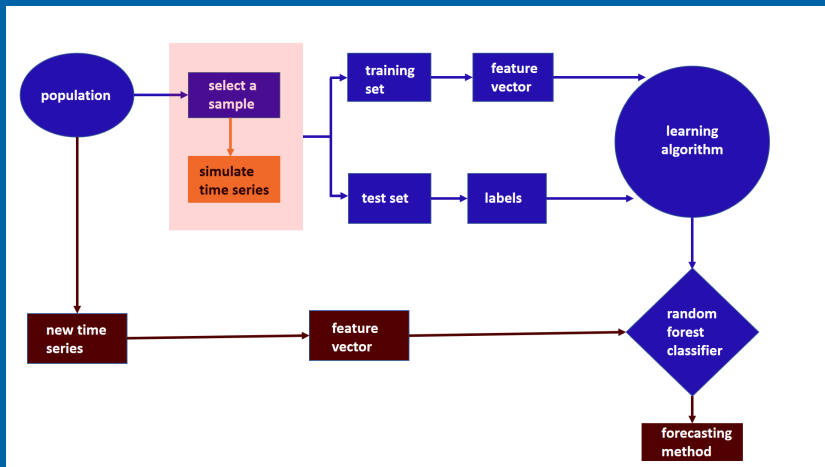
Methodology: “offline” part of the algorithm



Methodology: “online” part of the algorithm

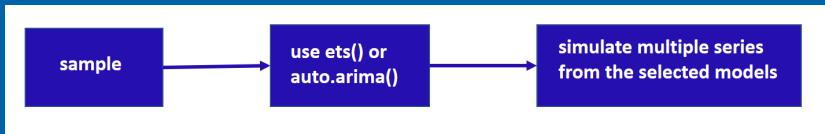


Methodology: reference set

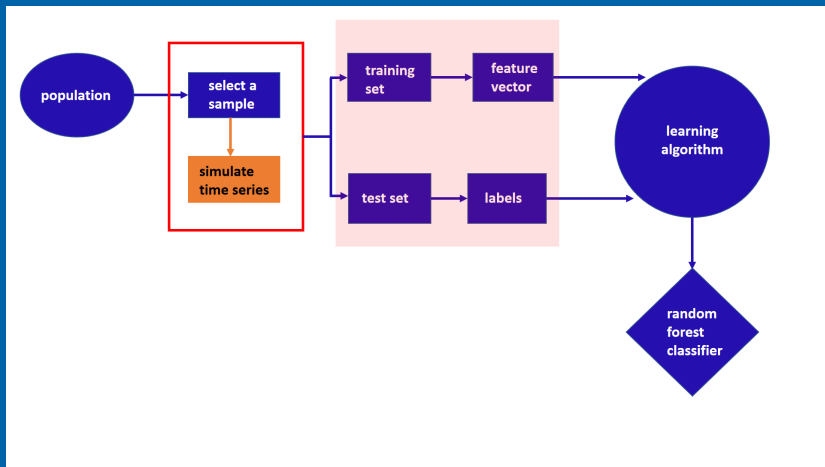


Augmenting the reference set with simulated series

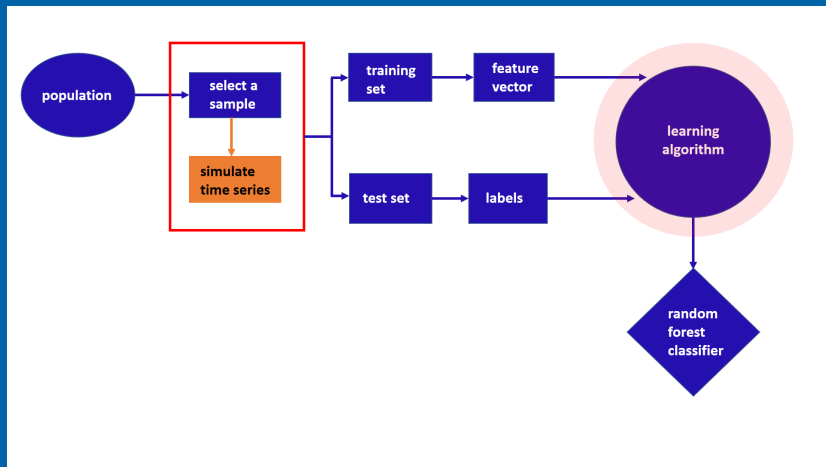
- when our sample is too small to build a reliable classifier
- when we wish to add more of some types of time series to the training set in order to get a more balanced sample
- How?



Methodology: features and class labels

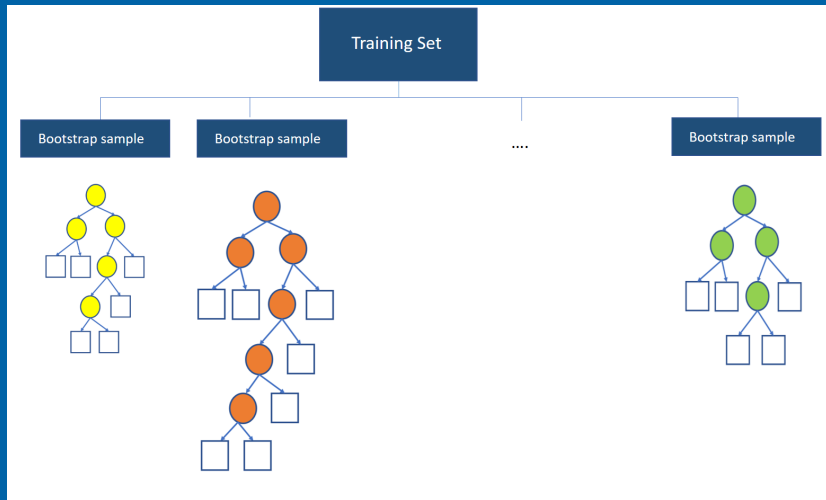


Methodology: random forest





Random forest



Preliminary study

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 - ▶ We consider random walks, white noise, ARIMA processes and ETS processes

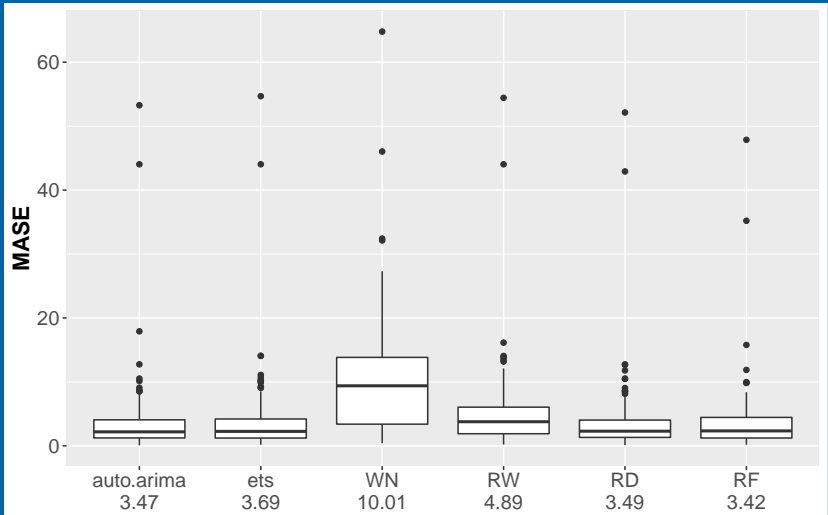
Preliminary study

- We consider non-seasonal time series
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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



What next?

- Develop a more comprehensive set of features that are useful in identifying different data generating processes.

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

What next?

- 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

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Slides shared online at:

<https://github.com/thiyangt/YSC-2017>

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