The Application of Machine Learning Methods to Time Series Forecasting

Bagging Exponential Smoothing Methods

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Abstract

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I want to thank my supervisor/parents/classmates...

Chapter 1

Introduction

Introduction and Research question

Machine learning methods have been developed and refined to the point that they now pose a serious challenge to classic statistical models in the area of forecasting. For example, Ahmed et al. (2010) came up with a large-scale comparison study based on the M3 competition dataset to compare the major machine learning models for time series forecasting. Exponential smoothing models are among the most frequently used forecasting methods. However, Bergmeir, Hyndman, and Benıtez (2016) argue that these models can be substantially outperformed for the purpose of forecasting by applying the bagging algorithm to a bootstrapped component of the initial time series to estimate an ensemble of exponential smoothing models and by combining the resulting point forecasts. This paper aims to investigate the performance of ensemble statistical learning methods for time series forecasting using a new dataset.

Preliminary overview of relevant literature

Januschowski et al. (2020) provide an overview of the spectrum of Machine learning and statistical methods and the boundaries and intersections in the context of forecasting. This distinction is a common way of classifying forecasting methods in the forecasting literature. However, the authors contend that there is no added value from such a classification of the methods and they encourage the scientific communities to collaborate more. Maasoumi and Medeiros (2010) present applications in Economics and Finance at the intersection of Statistical Learning and Econometrics. Inter alia, the authors analyze bagging and combination forecasts and find that bagging forecasts often deliver the lowest mean squared forecast errors.

Planned Methodology and Research Design

As suggested by Bergmeir et al. (2016), a Box-Cox transformation can be applied to the series in order to stabilize the variance of the time series and subsequently an STL decomposition is employed to break the time series down into the trend, the seasonal part and the remainder. Bootstrapping the remainder of the series is done to achieve stationarity. Furthermore, Galicia et al. (2019) suggest the use of

an ensemble time series forecasting model consisting of three components, which are decision trees, gradient boosted trees and Random Forests. For this model, the ensemble weights are computed by weighted least squares. They found that the ensemble outperforms its individual components. The three ensemble components can thus be employed for the purpose of this paper.

Data

The aim is to collect a time series data set in a monthly frequency or higher. Ideas would be to collect data to forecast energy prices, airline passenger demand, a financial time series or traffic data for instance. Hyndman (2020) argues that time series forecasting competitions have provided a medium for large-scale evaluation of forecasting methods and for the comparison of newly suggested methods with already existing state of the art forecasting methods. However, applying the suggested methods to the M3 or the M4 dataset used for those competitions seems to be a bit too broad in scope for the purpose of this paper.

Chapter 2

Chapter Two Title

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Appendix

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