MAS Thesis Introduction Draft
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Ensemble Methods to Improve Automated Time Series Forecasting

Abstract

There currently exist several “black box” software libraries for the automatic forecasting of time series. Popular among these is the ‘forecast’ package in R, which has functions to automatically fit several common classes of time series models, such as the autoregressive integrated moving average (ARIMA) and the family of exponential smoothing models, among others. It is often the case that what one gains from the ease in fitting these automatic methods comes as the cost of predictive performance. In this paper, we propose several methods to improve the prediction accuracy of automatic time series forecasting, all of which relate to creating ensembles of models automatically fit from the forecast package. We explore different ways that one can construct these ensembles and evaluate each on a benchmark time series dataset. In addition, we release an R software library that implements the methods discussed within this paper.

Introduction

Several scenarios exist that necessitate automatic time series forecasting. A manufacturing firm may need to generate monthly production forecasts for each of its products, of which there could be thousands. A hedge fund manager may need to forecast the price of a security every 30 seconds using the latest available stock data. In either case, the high volume of time series datasets or the frequency at which forecasts must be made represent too high a cost for a statistician to manually apply the classical Box-Jenkins methodology to fit an appropriate, causal, and invertible ARIMA model to each time series. In the first scenario, using such a methodology would consume too many man-hours of work, while in the second, a human could simply not keep up with the data.

In such situations, automatic ‘black box’ time series forecasting methods, like those implemented in the popular “forecast” R software library by Rob J. Hyndman, deliver a compelling value proposition — adequate forecasts can be made almost instantly by anyone. Even if these automatic methods do not perform as well as the ideal, manually fitted Box - Jenkins ARIMA model, the value they create by reducing forecast costs (in hours of work or time to model) can easily surpass the cost associated with implementing a less-than-ideal forecast. In the first scenario given above, 1000 adequate production-ready forecasts are better than 100 excellent forecasts and 900 missing values because the statistician ran out of time.

The work presented in this paper deals with how these ‘black box’ automatic methods can improved, so that a forecaster need not settle with adequate performance while still enjoying the benefits that black box methods provide. To that end, we explore several ways to create ensembles of four of the popular black box models included in the ‘forecast’ package to increase prediction accuracy over any single automatically fit model alone. To evaluate the performance of the ensembles, they will be tested with the M4-Competition dataset, which contains 100,000 univariate time series with periods ranging from hourly to yearly. Each series in the dataset is split into a training and test set, the latter of which will be used to evaluate loss using root mean squared error (RMSE), mean absolute percent error (MAPE), and mean absolute error (MAE).