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Time Series Methods in the R package MLR

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Abstract

The MLR package is a unified interface for machine learning tasks such as classification, regression, cluster analysis, and survival analysis. **mlr** handles the data pipeline of pre-processing, resampling, model selection, model tuning, and prediction. This paper details new methods for developing time series models in the **mlr**. Standard and novel tools such as auto-regressive and LambertW transform data generating processes, fixed and growing window cross validation, and forecasting models in the context of univariate and multivariate time series. Examples from forecasting competitions will be given in order to demonstrate the benefits of a unified framework for machine learning and time series.

Keywords: time series, model building, tuning parameters, R.

1. Introduction

There has been a rapid developement in time series methods over the last 25 years Gooijer and Hyndman (2006). Time series models have not only become more common, but more complex. The R language R Core Team (2015) has a large task view with many packages available for forecasting and time series methods. However, without a standard framework, many packages have their own sub-culture of style, syntax, and output. The **mlr** Bischl, Lang, Richter, Bossek, Judt, Kuehn, Studerus, and Kotthoff (2015) package, short for Machine Learning in R, works to give a strong syntatic framework for the modeling pipeline. By automating many of the standard tools in machine learning such as preprocessing and cross validation, **mlr** reduces error in the modeling process that is derived from the user.

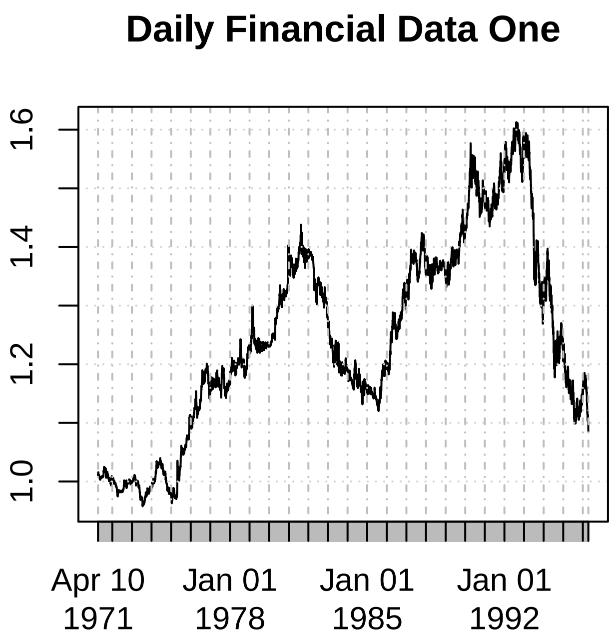
While there are some time series methods available in the **caret** from Jed Wing, Weston, Williams, Keefer, Engelhardt, Cooper, Mayer, Kenkel, the R Core Team, Benesty, Lescarbeau, Ziem, Scrucca, Tang, and Candan. (2015), development of full on forecasting models in **caret** is difficult due to computational constraints and design choices. The highly modular structure of **mlr** makes it the best choice for implementing time series methods and models. This paper will show how using **mlr**'s strong syntatic structure allows for time series packages such as **forecast** Hyndman and Khandakar (2008) and **rugarch** Ghalanos (2015) to use machine learning methedologies such as automated parameter tuning, data preprocessing, model blending, cross validation, performance evaluation, and parallel processing techniques for decreasing model build time.

2. Forecasting Example with the M4 Competition

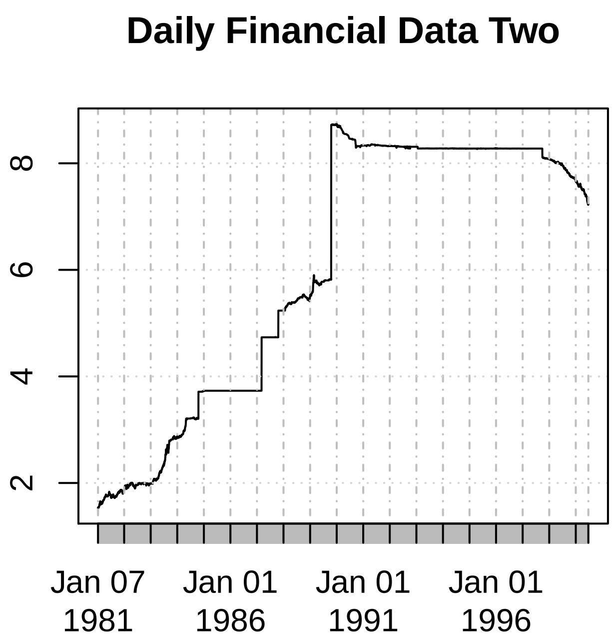
Professional forecasters attempt to predict the future of a series based on its past values. While forecasting is commonly associated with economics and finance, the ability to predict the future is very important for a number of fields. The Makridakis competitions Makridakis and Hibon (2000) are forecasting challenges organized by the International Institute of Forecasters and led by Spyros Makridakis to evaluate and compare the accuracy of forecasting methods. The most recent of the competitions, the M4 competition, contains 10,000 time series on a yearly, quarterly, monthly, and daily frequency and areas such as finance, macroeconomics, microeconomics, and industry. For our purposes we will look at two particular daily financial series, one with 9136 observations from April 10th, 1971 to April 13th, 1996 and another with 6742 observations from January 7th, 1981 to June 23rd, 1999. Each series has a forecasting of 328 and 242 periods into the future, respectively.

```
library(M4comp)
library(xts)
library(lubridate)
m4Fin1 <- M4[[28]]
m4Train1 <- xts(m4Fin1$past, as.POSIXct("1971-04-10") + days(0:I(length(m4Fin1$past)-
1)))
m4Test1 <- xts(m4Fin1$future, as.POSIXct("1996-01-15") + days(0:I(length(m4Fin1$future)-
1)))

m4Fin2 <- M4[[29]]
m4Train2 <- xts(m4Fin2$past, as.POSIXct("1981-01-07") + days(0:I(length(m4Fin2$past)-
1)))
m4Test2 <- xts(m4Fin2$future, as.POSIXct("1999-06-23") + days(0:I(length(m4Fin2$future)-
1)))
plot(m4Train1, main = "Daily Financial Data One")
```




```
plot(m4Train2, main = "Daily Financial Data Two")
```



These two series were chosen for their large time features and stark contrast. Our data set should be large enough that the tuning method can take multiple windows of the data. Some series in M4 only contain 12 observations, which is not enough data to accurately train a model. These two time series were chosen as they are the two largest ones in the M4 competitions data set. We can see figure one is what most people imagine when they think of a time series. Figure two shows a series which appears to have a sort of step feature. The stark difference between the time process of the two series will allow us to investigate whether the methods in **mlr**'s forecasting framework can find the appropriate model. The data can be found in the package **M4comp** BenTaieb (2016) under sets twenty eight and twenty nine.

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