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

The Makridakis competitions Makridakis and Hibon (2000) are forecasting challenges orga-
nized 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 fre-
quency 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 and
another with 6742 observations.

```r
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")
```
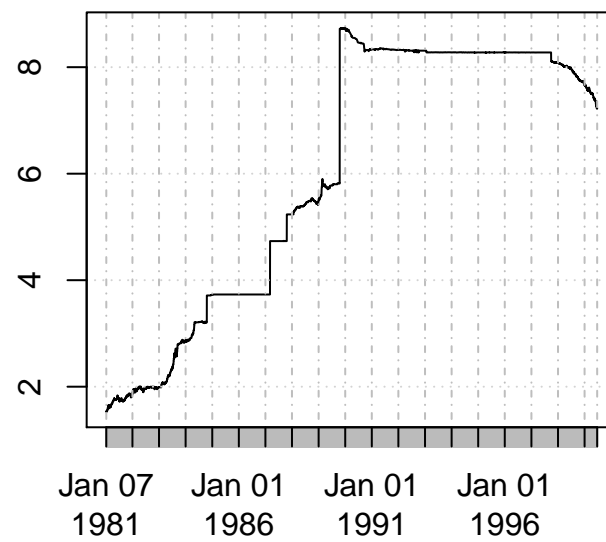
Daily Financial Data One
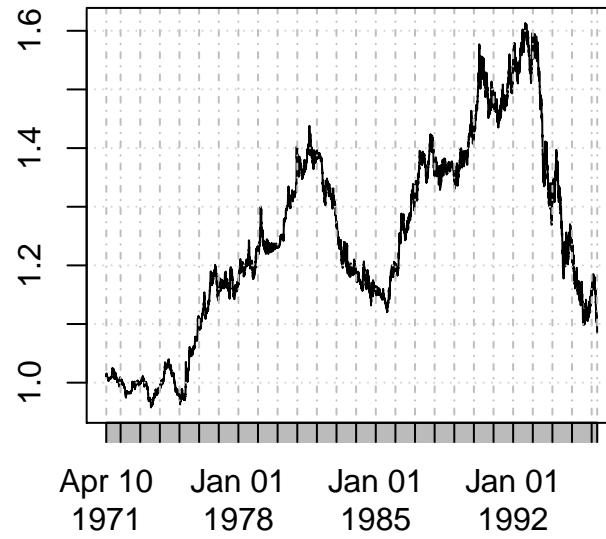

```
plot(m4Train2, main = "Daily Financial Data Two")
```

Daily Financial Data Two

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