USING R LANGUAGE BSTS PACKAGE FOR MODELLING BAYESIAN STRUCTURAL TIME SERIES

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Introduction

Forecasting is an important tool in various fields, in particular economics, finance, meteorology, climatology, data science and other subject areas. Prediction refers to the process of estimating future values or states of a system based on available data and knowledge of past values and trends. Predictive analysis allows for more informed decision-making based on probabilistic estimates of future system development, which can be useful for planning, resource management and strategic decision-making.

Currently, time series are one of the most common objects of analysis. This necessitates the development of effective methods for estimating time series parameters, which will provide better predictions of measured parameters and identify patterns in their changes. There are many models for analyzing and forecasting time series. One promising approach in time series analysis is to represent it as a Bayesian structural time series (BSTS model) [1-8].

BSTS model

In Bayesian structural models, the time series is represented as a sum of unobservable components, which

The fitting of structural time series models is done using the Kalman filter and the Markov chain Monte Carlo

Software experiments

The applicability of the BSTS model to estimate the parameters of the temperature time series was investiga

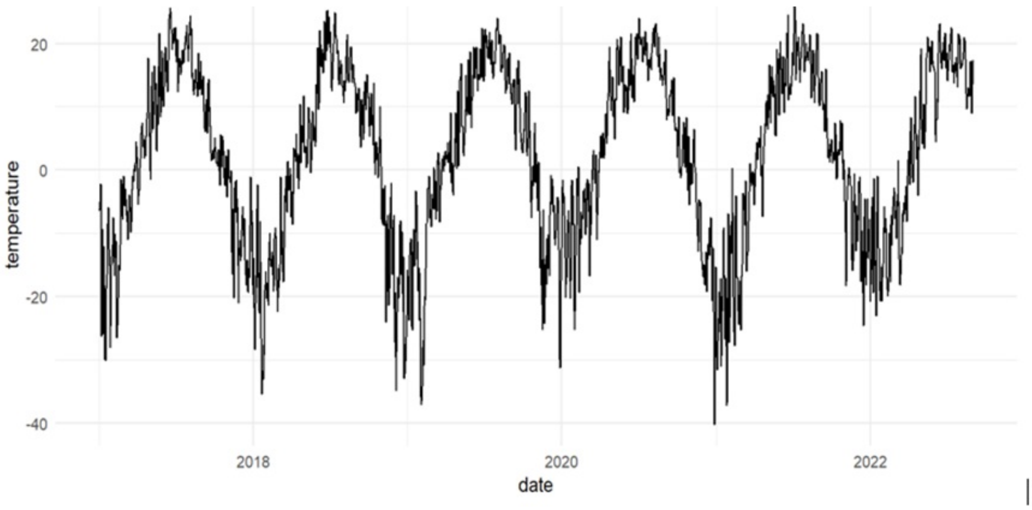

Figure 1. Average daily air temperatures in Tomsk

First, import the data and present it as a time series.

```
mydata3 <- read_excel("E:/Desktop/456.xlsx",
col_types = c("date“, “numeric”)) %>%
as_tsibble(., key = NULL, index = time, regular = FALSE)
```

Next, we decompose the time series to understand its structure.

```
de <- decompose(mydata3)
plot(de)
```

Figure 2 shows the result of decomposition of this series. The figure shows that this series has an obvious a

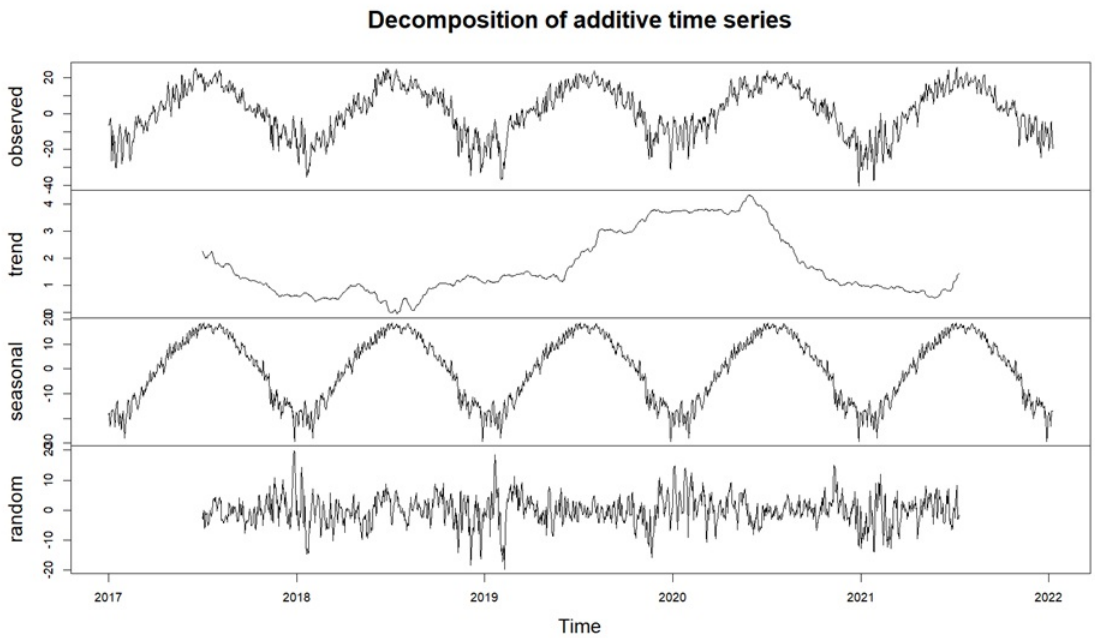

Figure 2. The result of time series decomposition

Then we split the data into a training sample and a validation sample (Fig. 3). The forecast period is set to 2

```
mydata3 <- read_excel("E:/Desktop/456.xlsx",

col_types = c("date“, “numeric”)) %>%

as_tsibble(., key = NULL, index = time, regular = FALSE)

de <- decompose(mydata3)

plot(de)

temp <- mydata3 %>%

index_by(dt = as.Date(time)) %>%

summarise(y = temperature)

cut_point <- as.Date(max(temp$dt)) — 200 #training time — 200 days

temp_train <- temp %>%

filter(as.Date(dt) <= cut_point)

temp_test <- temp %>%

filter(as.Date(dt) > cut_point)

dplyr::bind_rows(mutate(temp_train, dataset = “train”),

mutate(temp_test, dataset = “test”)) %>%

ggplot(aes(dt, y, col = dataset)) +

geom_line() + geom_point(alpha = 0.4) +

theme_minimal() +

scale_color_manual(values = c("blue“, “black”))

temp_1 <- temp_train$y

dt_1 <- temp_train$dt
```

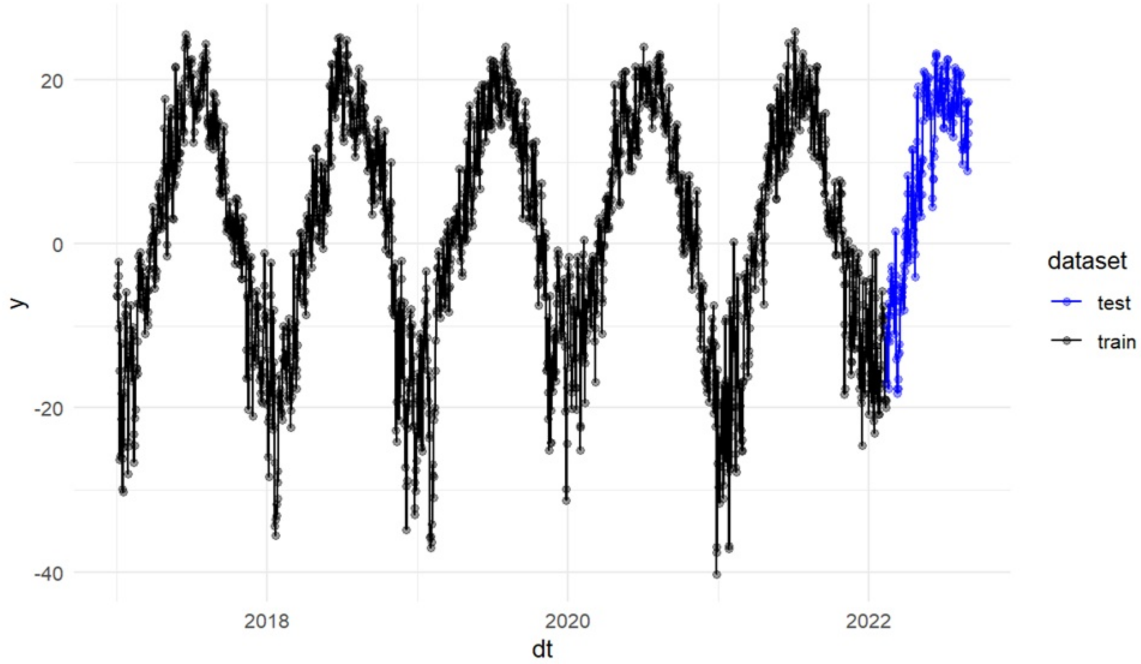

Figure 3. Training and test samples

Next comes the fitting of the model.

```
ss <- list()

ss <- AddSeasonal(ss, temp_1, nseasons=12,season.duration = 30)

ss <- AddAutoAr(ss,temp_1,lags = 2)

M4.5<- bsts(temp_1, ss,

timestamps = dt_1,

niter = 700,ping = 50, seed = 511)

plot(M4.5)
```

Figure 4 shows the result of the model fitting.

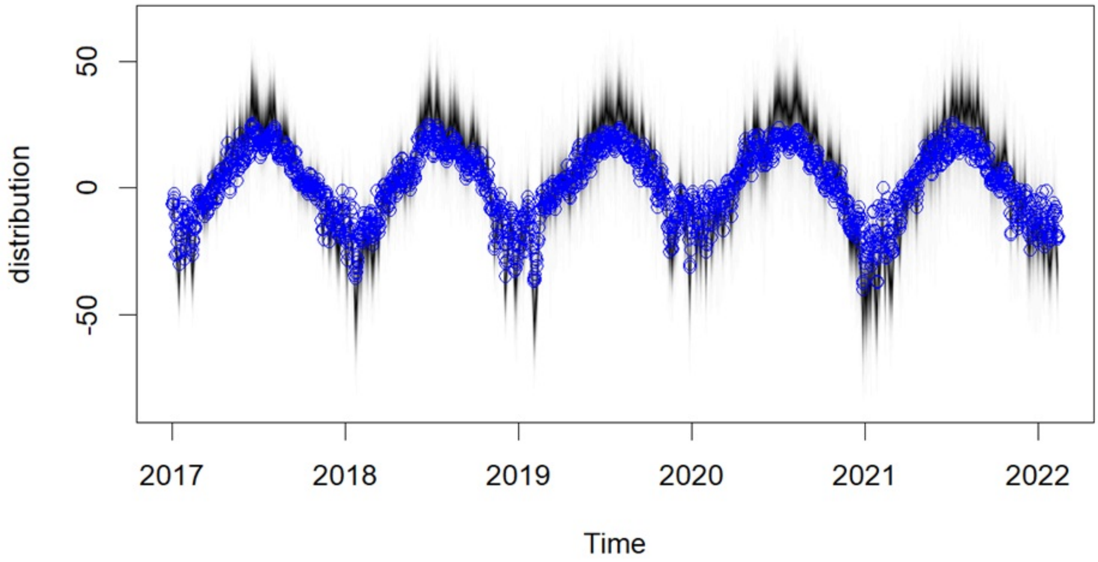

Figure 4. Result of model fitting

```
M_pred<- predict(M4.5, horizon = 200)

plot(M_pred,ylim = c(-50,50),plot.original = 50)

with(temp_test, points(dt, y, pch = 200, col = “yellow”))
```

Next are the forecast and the visual assessment of the forecast. Figure 5 shows the result of the forecast. B

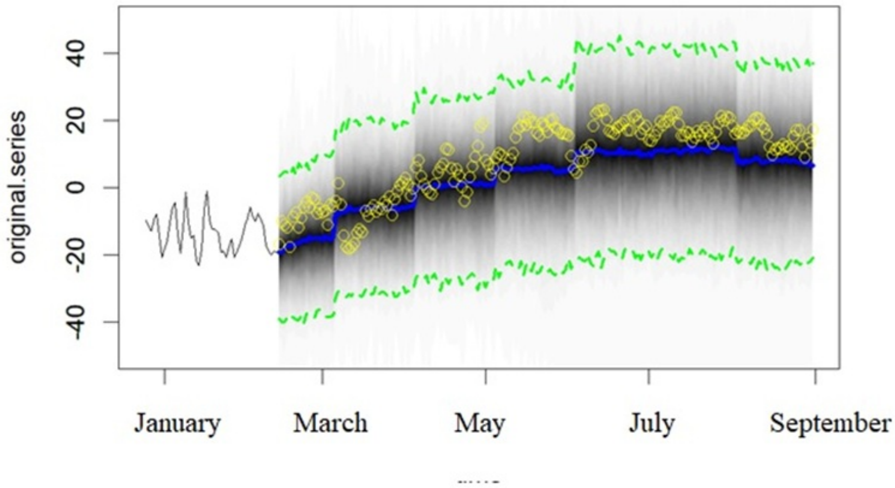

Figure 5. Forecast result

Next, we calculate the mean absolute specific error (MAPE).

```
mape <- function(observed, predicted){

mean(abs(observed — predicted)/observed)

}

sapply(list("M4.5″ = M_pred_4.5),

mape, observed = temp_test$y ) %>%

round(., 5)
```

Figure 6 shows the resulting error value.

```
   M4.5
0.16201
```

Figure 6. Mean absolute specific error

Conclusion

A software experiment scheme was developed to build and study a Bayesian structural time series model (E

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