



Adventures in Bayesian Structural Time Series

Part 4: Analyzing SST Data With Regression

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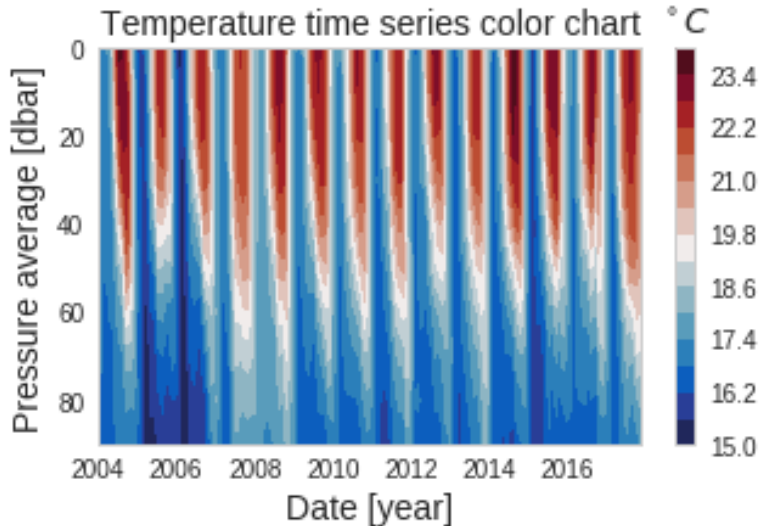




- ⊠ SST data with covariates
- ⊠ Use **bsts** to
 - ⊠ Fit structural model with regression
 - ⊠ Regression posterior
 - ⊠ Forecast
 - ⊠ Custom regresson prior

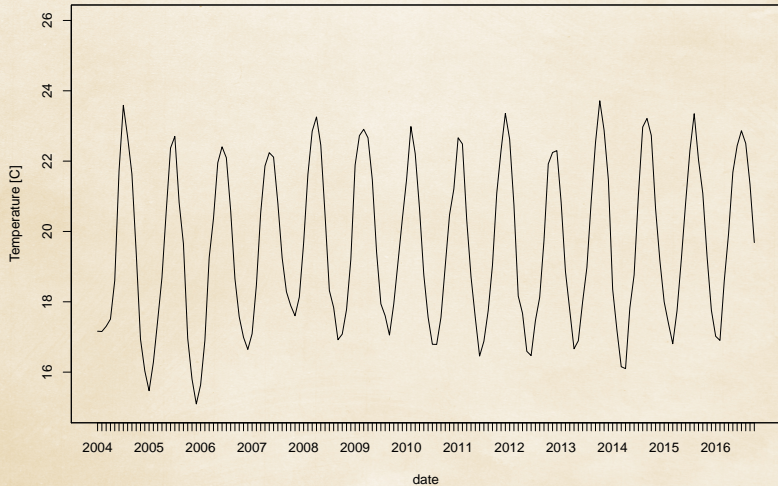


- ⊠ Sea Surface Temperature near Gibraltar
- ⊠ Aggregated monthly
- ⊠ January 2004 to November 2017
- ⊠ Covariates: depth at 10, 20, ..., 90 meters





SST of Gilbralter region





```
library(readr)
library(bsts)

gib <- read_csv("data/gilbralter_time_series_r.csv",
               col_types = cols(startDate = col_skip(),
                                timeIdx = col_skip()))
names(gib) <- c('SST', '10', '20', '30', '40',
               '50', '60', '70', '80', '90')
gib <- zooreg(gibraltar, start = c(2004, 1, 1),
             end = c(2017, 11, 29),
             frequency = 12)
```

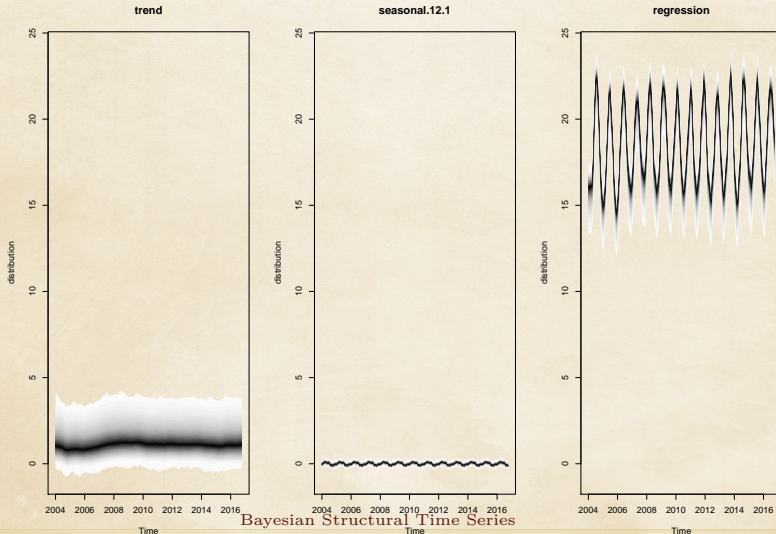


Model Fitting

```
ss <- AddLocalLinearTrend(list(), gib$SST)
ss <- AddSeasonal(ss, gib$SST, nseasons = 12)
model1 <- bstts(SST ~ ., state.specification = ss,
                data = gib, niter = 1000, ping = 0)
```

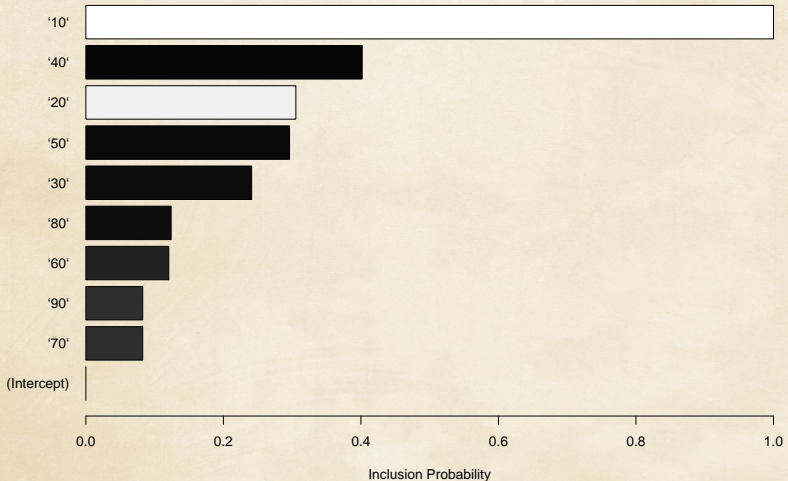



```
plot(model1, 'components')
```



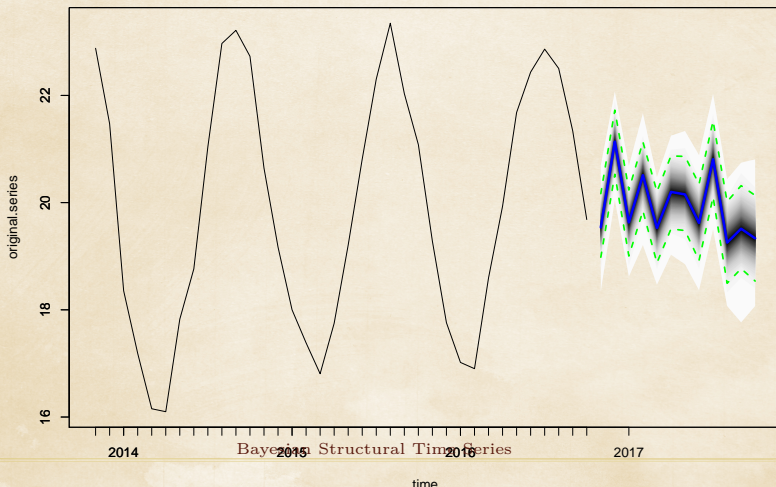


```
plot(model1, 'coefficients')
```





```
model1_pred <- predict(model1, newdata = newdata,  
                        horizon = 12)  
plot(model1_pred, plot.original = 36)
```

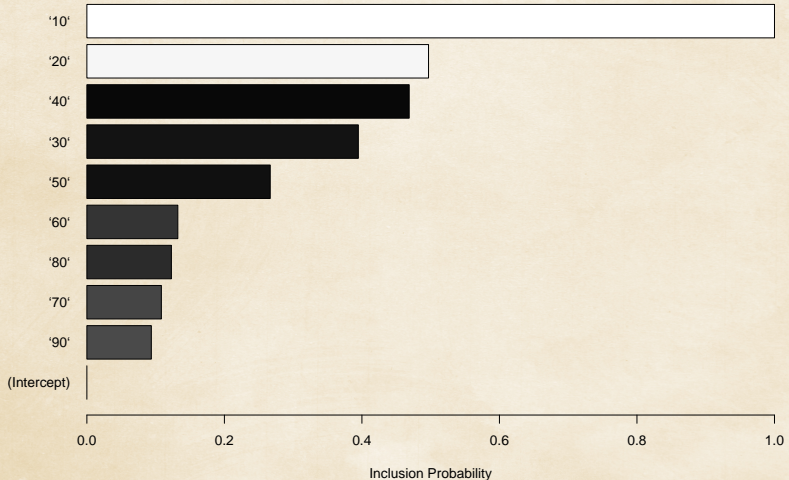




```
model2 <- bstS(SST ~., state.specification = ss,  
               data = gib, niter = 1000, ping = 0,  
               expected.model.size = 2)
```



```
plot(model2, 'coefficients')
```





```
model3 <- bstS(SST ~., state.specification = ss,  
               data = gib, niter = 1000, ping = 0,  
               prior.inclusion.proBABILITIES =  
                 c(0.01, 0.5, 0.3, 0.3, 0.1, 0.1,  
                   0.1, 0.1, 0.1, 0.1))
```



```
plot(model3, 'coefficients')
```

