San Diego State University

Adventures in Bayesian Structural Time Series

Part 3: Analyzing SST Data

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Outline

- SST Data

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- Use `bsts` for

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  - Fit

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    - local level

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  - Forecast
  - Model Comparison

SST Data

- Sea Surface Temperature near Gibraltar

SST Data

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- Aggregated every 12 days

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- January 2004 to November 2017

SST Data

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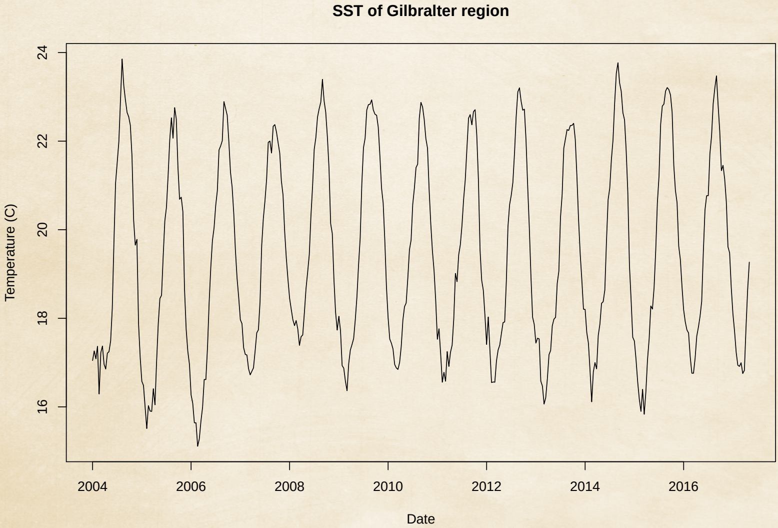
- Sea Surface Temperature near Gibraltar
- Aggregated every 12 days
- January 2004 to November 2017
- Obtained from Argovis

SST Data



SST of Gilbralter region
Temperature (C)
16
18
20
22
24
2004
2006
2008
2010
2012
2014
2016
Date

Setup

```r
library(readr)
library(bsts)
# bsts also loads BoomSpikeSlab, Boom, MASS, zoo, xts


gilbralter <- read_csv("data/gilbraltersimple.csv")
gilt <- ts(gilbralter$tempMean, start=c(2004,1,13),
           end=c(2017, 11, 25), frequency=30)
plot(gilt, main='SST of Gilbralter region',
     xlab='Date',
     ylab='Temperature (C)')
```

Model Fitting

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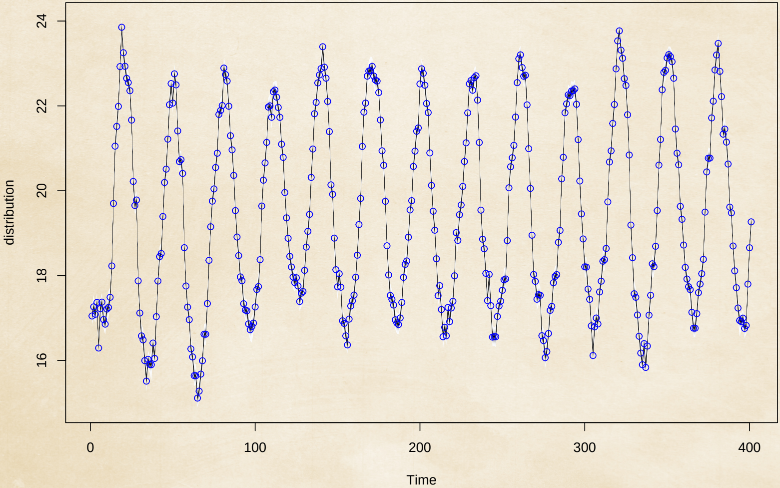
Local Level Model

$$y_t = \mu_t + \varepsilon_t \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2)$$
$$\mu_{t+1} = \mu_t + \xi_t \qquad \xi_t \sim N(0, \sigma_\xi^2)$$

```
ll_ss <- list()
ll_ss <- AddLocalLevel(state.specification = ll_ss,
                       y = gilt)
ll_fit <- bsts(gilt, state.specification = ll_ss,
               niter = 1e3)
```

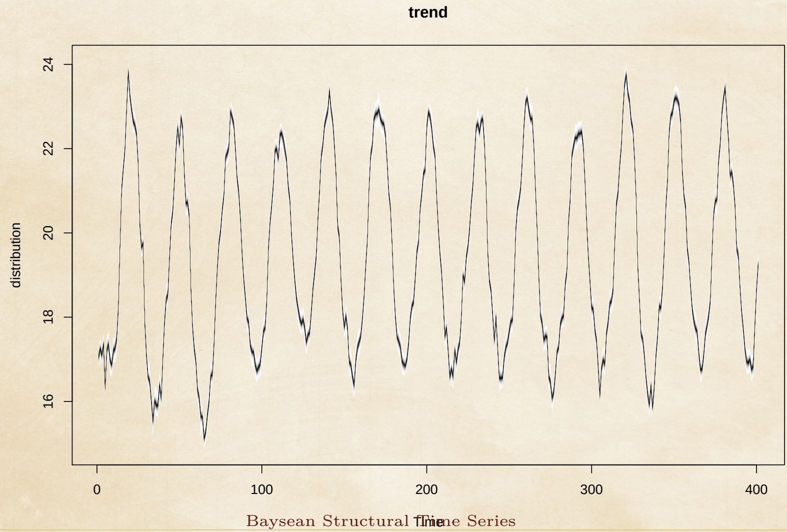
Model Plotting

```
plot(ll_fit)
```



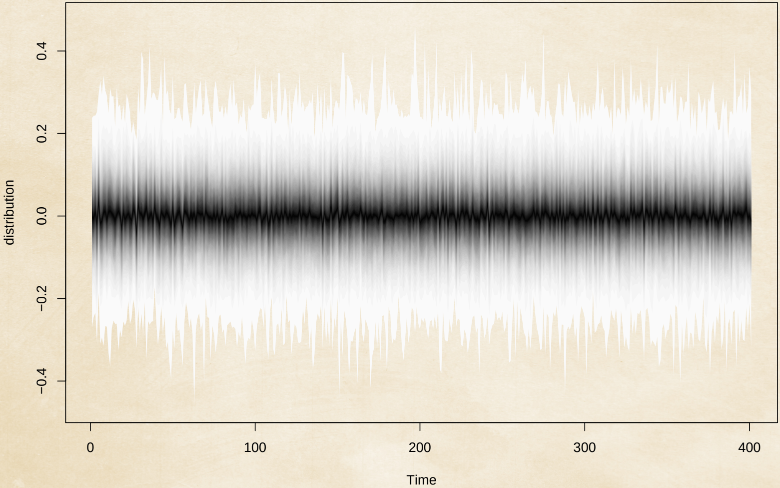
Model Plotting

```r
plot(ll_fit, 'components')
```



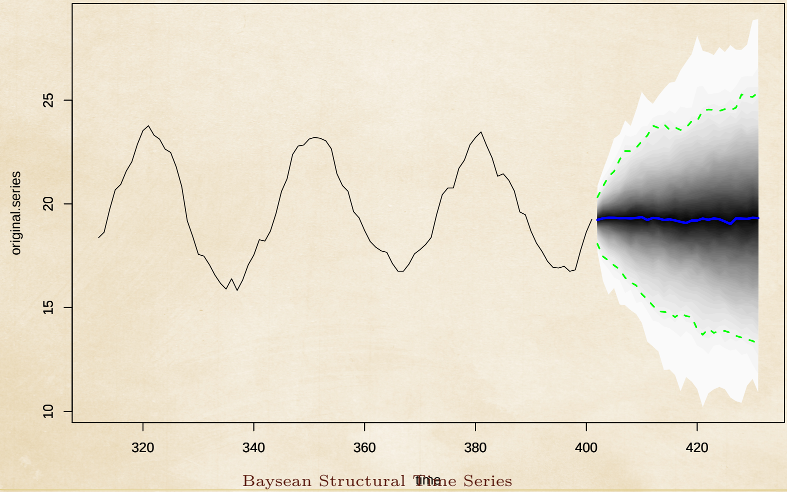
Model Plotting

```
plot(ll_fit, 'residuals')
```



Forecasting

```r
ll_pred <- predict(ll_fit, horizon = 30)
plot(ll_pred, plot.original = 90)
```



Model Fitting

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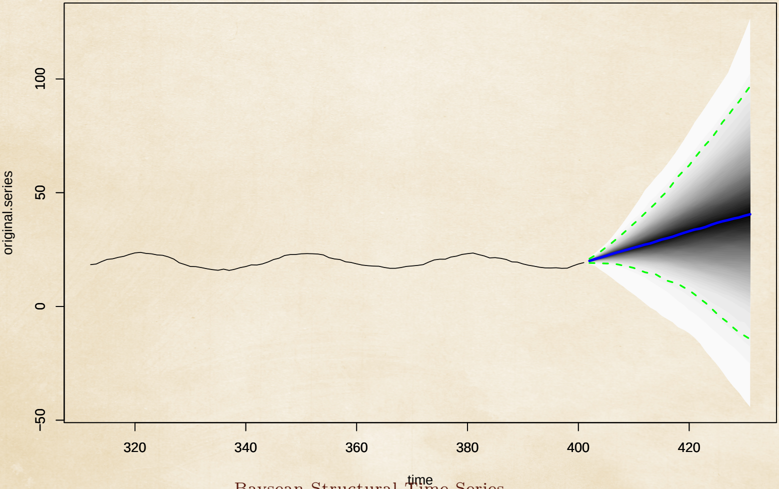
Local Linear Trend Model

$$
\begin{aligned}
y_t &= \mu_t + \varepsilon_t & \varepsilon_t &\sim N(0, \sigma_\varepsilon^2) \\
\mu_{t+1} &= \mu_t + \nu_t + \xi_t & \xi_t &\sim N(0, \sigma_\xi^2) \\
\nu_{t+1} &= \nu_t + \zeta_t & \zeta_t &\sim N(0, \sigma_\zeta^2)
\end{aligned}
$$

```r
llt_ss <- list()
llt_ss <- AddLocalLinearTrend(
  state.specification = llt_ss, y = gilt)
llt_fit <- bsts(gilt, state.specification = llt_ss,
                niter = 1e3)
```

Forecasts

```r
llt_pred <- predict(llt_fit, horizon = 30)
plot(llt_pred, plot.original = 90)
```



Model Fitting

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Local Trend With Seasonality

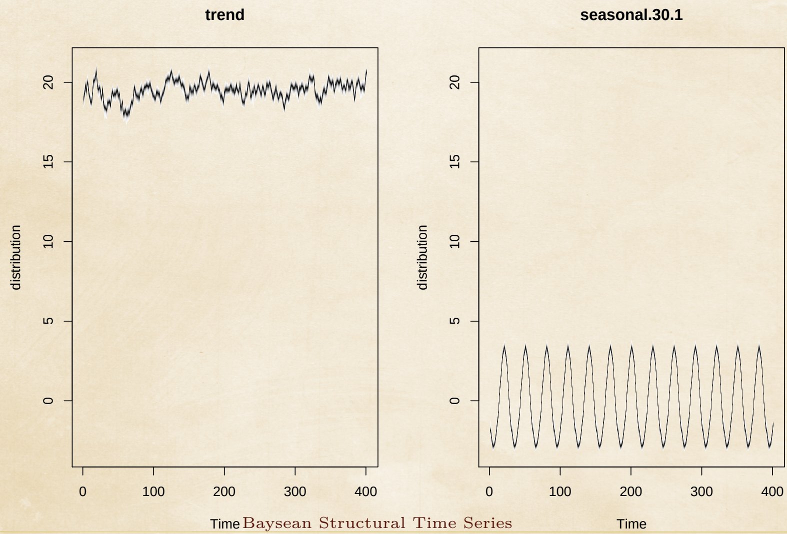
$$y_t = \mu_t + \tau_t + \varepsilon_t \qquad \zeta_t \sim N(0, \sigma_\varepsilon^2)$$

$$\tau_t = -\sum_{s=1}^{S-1} \tau_{t-s} + \omega_t \qquad \tau_t \sim N(0, \sigma_\omega^2)$$

```
lts_ss <- list()
lts_ss <- AddLocalLinearTrend(lts_ss, y = gilt)
lts_ss <- AddSeasonal(lts_ss, gilt, nseasons = 30)
lts_fit <- bsts(gilt, state.specification = lts_ss,
                niter = 1e3)
```

Components

```
plot(lts_fit, 'components')
```



Forecasts

```r
lts_pred <- predict(lts_fit, horizon = 30)
plot(lts_pred, plot.original = 90)
```