# Adventures in Bayesian Structural Time Series

*Part 3: Analyzing SST Data*

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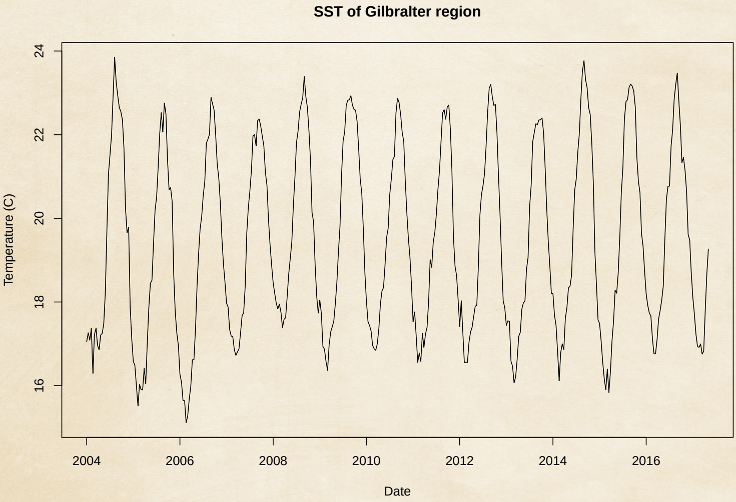
# Outline

- SST data.
- Model fitting of SST data, whose components include: local level, local linear trend, and seasonal trend.
- Generating a posterior distribution of our model time series
- Some heuristic comparisons between the different models.

# SST Data


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

# SST Data

- SST data come from Argo floats
- Aggregated every 12 days
- January 2004 to November 2017
- Obtained from www.Argovis.com
- Learn more about Argovis by watching a tutorial at `https://www.youtube.com/watch?v=IlNJOowuTHM&t=0s`

# 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)')
```

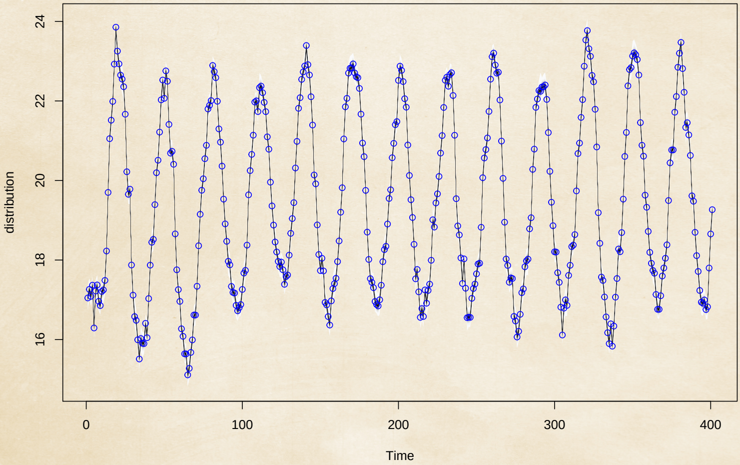
# Model Fitting

## Local Level Model

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

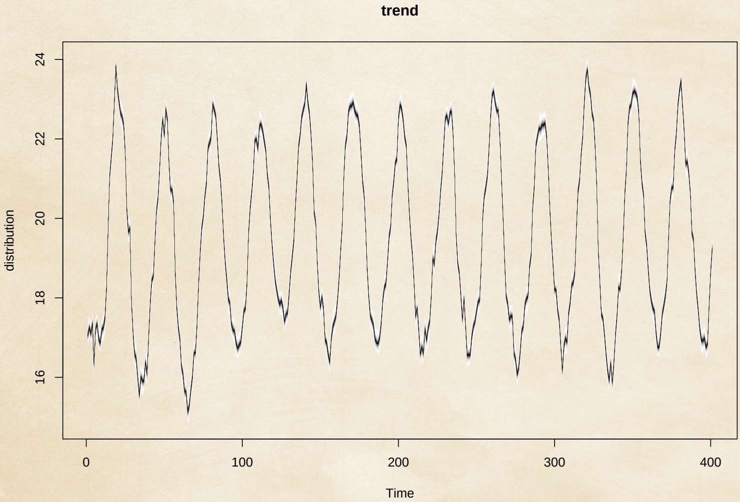
```r
ll_ss <- list()
ll_ss <- AddLocalLevel(state.specification = ll_ss,
                       y = gilt)
ll_fit <- bsts(gilt, state.specification = ll_ss,
               niter = 1e3)
```

```
plot(ll_fit)
```



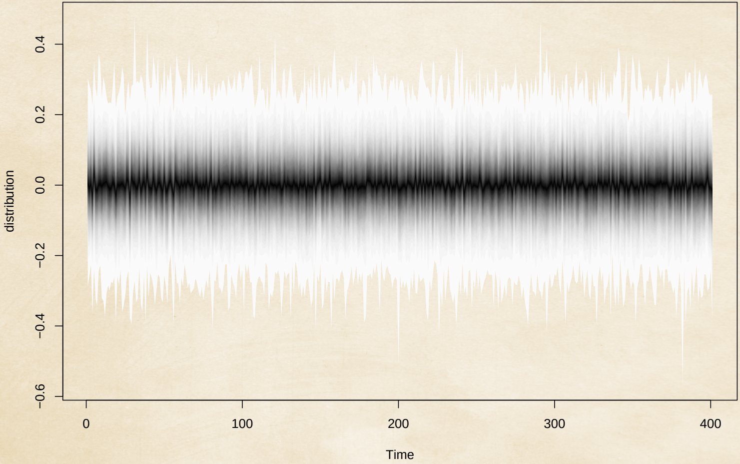
# Model Plotting

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



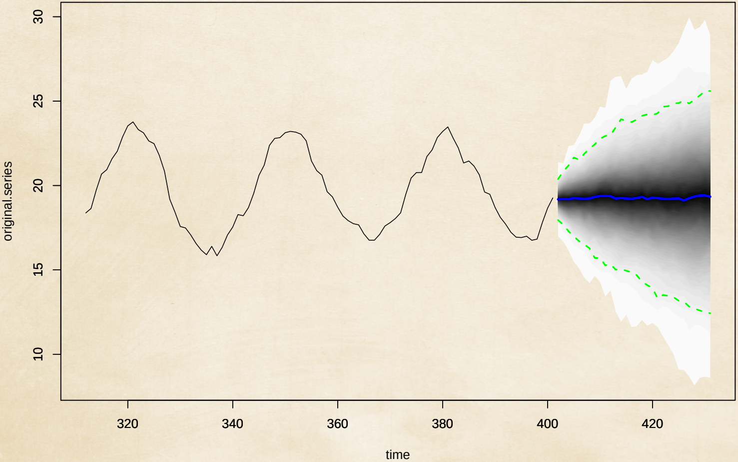
# Model Plotting

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



# Forecasting

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



# Model Fitting

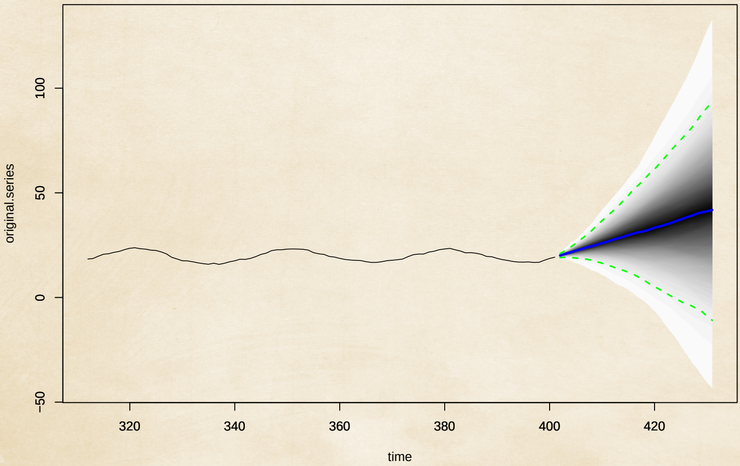
## Local Linear Trend Model

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

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

# Forecasts

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



## Local Trend With Seasonality

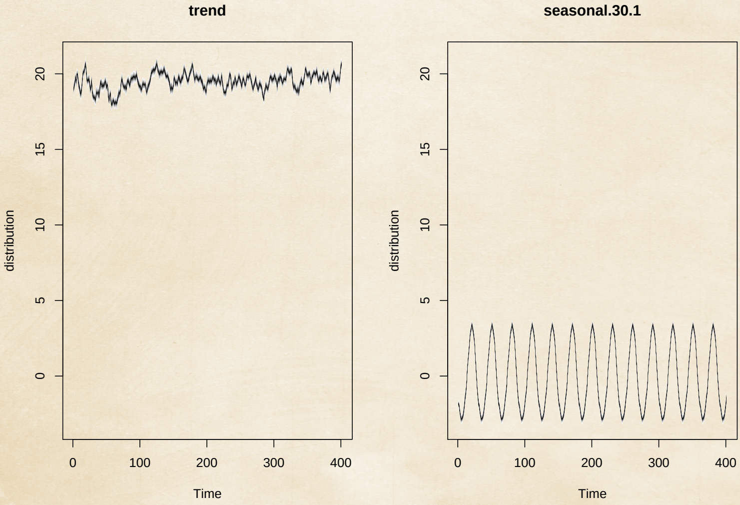
$$y_t = \mu_t + \tau_t + \varepsilon_t \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2)$$

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

```
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)
```

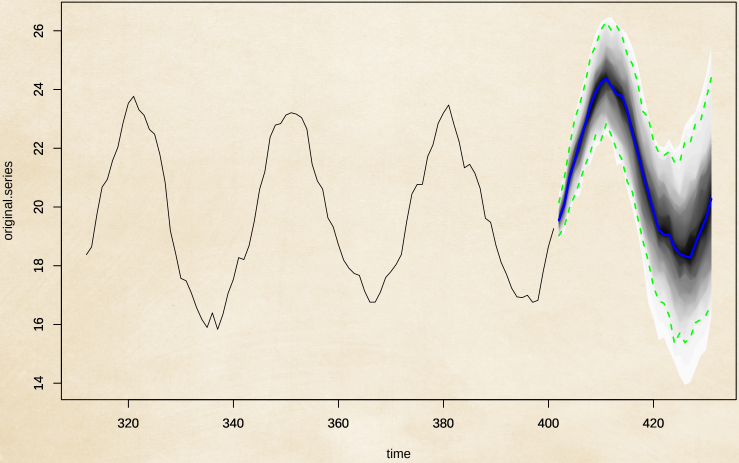
# Components

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



# Forecasts

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



# Model Comparison

```
CompareBstsModels(lwd = 4, model.list = list(
  level = ll_fit, trend = llt_fit, season = lts_fit),
  colors = c("forestgreen", "firebrick", "blue4"))
```