<http://robjhyndman.com/hyndsight/dailydata/>

看一下文章评论

<http://robjhyndman.com/papers/ComplexSeasonality.pdf>

<http://stats.stackexchange.com/questions/163371/work-with-results-of-tbats-decomposition/164423#164423>

http://stats.stackexchange.com/questions/222199/how-to-interpret-tbats-model-results-and-model-diagnostics?rq=1

http://stats.stackexchange.com/questions/55716/interpreting-time-series-decomposition-using-tbats-from-r-forecast-package?rq=1

http://stats.stackexchange.com/questions/213409/decomposing-a-multi-seasonal-time-series-using-tbats-in-r?rq=1

**http://stats.stackexchange.com/questions/96867/increasing-the-accuracy-of-tbats-forecasts-by-factoring-for-correlations-betwe?rq=1**

When the time series is long enough to take in more than a year, then it may be necessary to allow for annual seasonality as well as weekly seasonality. In that case, a multiple seasonal model such as TBATS is required.

y <-msts(x, seasonal.periods=**c**(7,365.25))

fit<-tbats(y)

fc<- forecast(fit)

**plot**(fc)

This should capture the weekly pattern as well as the longer annual pattern. The period 365.25 is the average length of a year allowing for leap years. In some countries, alternative or additional year lengths may be necessary. For example, with the Turkish electricity data analysed in [De Livera et al (JASA 2011)](http://robjhyndman.com/papers/complex-seasonality/), we used three seasonal periods: 7, 354.35 and 365.25. The period 354.37 is the average length of the Islamic calendar.

Capturing seasonality associated with moving events such as Easter or the Chinese New Year is more difficult. Even with monthly data, this can be tricky as the festivals can fall in either March or April (for Easter) or in January or February (for the Chinese New Year). The usual seasonal models don’t allow for this, and even the complex seasonality discussed in my JASA paper assumes that the seasonal patterns occur at the same time in each year. The best way to deal with moving holiday effects is to use dummy variables. However, neither ETS nor TBATS models allow for covariates. A state space model of the same form as TBATS but with multiple sources of error and covariates could be used, but I don’t have any R code to do that.

Instead, I would use a regression model with ARIMA errors, where the regression terms include any dummy holiday effects as well as the longer annual seasonality. Unless there are many decades of data, it is usually reasonable to assume that the annual seasonal shape is unchanged from year to year, and so Fourier terms can be used to model the annual seasonality. Suppose we use K=5 Fourier terms to model annual seasonality, and that the holiday dummy variables are in the vector holiday with 100 future values in holidayf. Then the following code will fit an appropriate model.

|  |
| --- |
| y <-**ts**(x, **frequency**=7)  z <-fourier(**ts**(x, **frequency**=365.25), K=5)  zf<-fourierf(**ts**(x, **frequency**=365.25), K=5, h=100)  fit <-auto.arima(y, xreg=**cbind**(z,holiday), seasonal=FALSE)  fc <- forecast(fit, xreg=**cbind**(zf,holidayf), h=100) |

The order K can be chosen by minimizing the AIC of the fitted model.

说明：

多季节效应—TBATS模型

多季节效应，包括年度季节性与周期季节性

针对节假日效应，模型通常假设节假日日期是固定不变的，然而实际上是变化的，这里作者提出采用虚拟变量是比较可取的方式，但是TBATS模型不允许协变量存在，状态空间的TBATS模型可以实现，不过作者还没有相关代码。针对这种情况，作者通常拟合arima模型，外生变量设置为节假日效应的虚拟变量和长周期的年度季节效应。除非有几十年的数据，那么可以认为“假设年度季节效应是不变的”是合理的，因此，Fourier可用来对年度季节性建模。