Spring 2013 Statistics 153 (Time Series) : Lecture Three

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1 Last Class

We looked at ways of dealing with trend in time series models. The simplest model for trend is $X_t = m_t + Z_t$ where m_t is a deterministic trend function and Z_t is white noise. We looked at two main ways of estimating the trend function m_t: (a) parametric and (b) nonparametric (smoothing and isotonic estimation for monotone trends).

We also looked at differencing as a way of eliminating trend in data leading to trendless residuals. We will study later ways of modeling such trendless residuals.

2 Notation for Differencing

It is useful to follow the notation ∇ for differencing:

$$\nabla X_t = X_t - X_{t-1} \qquad \text{for } t = 2, \dots, n$$

and second differencing corresponds to

$$\nabla^2 X_t = \nabla(\nabla X_t) = \nabla X_t - \nabla X_{t-1} = X_t - 2X_{t-1} + X_{t-2} \qquad \text{for } t = 3, \dots, n.$$

Linear trends disappear under the operation ∇. Quadratic trends disappear with the operation ∇^2.

Suppose the data $\nabla^2 X_t$ appear like white noise, how would you obtain a forecast for X_{n+1}?

3 Stochastic Model for Trend

One can also consider models $X_t = m_t + Z_t$ where m_t is a stochastic trend function as opposed to a deterministic trend function. A popular choice is:

$$m_t = m_{t-1} + \delta + W_t$$

where $\delta \in \mathbb{R}$ is a fixed constant and W_t is white noise. This is an example of a state space model. When $\delta = 0$, this is called the local level model.

The noise $\{W_t\}$ is called evolution error and the noise $\{Z_t\}$ is known as observational error. It is assumed that these two error processes are independent. In some appications, this model might be more suitable than any deterministic trend model.

Observe that the differenced series for X_t is:

$$\nabla X_t = X_t - X_{t-1} = m_t - m_{t-1} + Z_t - Z_{t-1} = \delta + W_t + Z_t - Z_{t-1}.$$

∇X_t is thus a detrended series. Therefore, differencing also works with stochastic models for trend.

4 Models for Seasonality

Many time series datasets exhibit seasonality. Simplest way to model this is: $X_t = s_t + Z_t$ where s_t is a periodic function of a known period d i.e., $s_{t+d} = s_t$ for all t. Such a function s models seasonality. These models are appropriate, for example, to monthly, quarterly or weekly data sets that have a seasonal pattern to them.

This model, however, will not be applicable for datasets having both trend and seasonality which is the more realistic situation. These will be studied a little later.

Just like the trend case, there are three different approaches to dealing with seasonality: fitting parametric functions, smoothing and differencing.

4.0.1 Fitting a parametric seasonality function

The simplest periodic functions of period d are: $a\cos(2\pi ft/d)$ and $a\sin(2\pi ft/d)$. Here f is a positive integer. The quantity a is called *Amplitude* and f/d is called *frequency* and its inverse, d/f is called *period*. The higher f is, the more rapid the oscillations in the function are.

More generally,

$$s_t = a_0 + \sum_{f=1}^{k} \left(a_j \cos(2\pi ft/d) + b_j \sin(2\pi ft/d)\right) \tag{1}$$

is a periodic function. Choose a value of k (not too large) and fit this to the data.

For $d = 12$, there is no need to consider values of k that are more than 6. With $k = 6$, every periodic function with period 12 can be written in the form (1). More on this when we study the frequency domain analysis of time series.

4.0.2 Nonparametric seasonality function estimation

Because of periodicity, the function s_t only depends on the d values $s_1, s_2, \dots, s_d$. Clearly s_1 can be estimated by the average of $X_1, X_{1+d}, X_{1+2d}, \dots$. For example, for monthly data, this corresponds to estimating the mean term for January by averaging all January observations. Thus

$$\hat{s}_i := \text{average of } X_i, X_{i+d}, X_{i+2d}, \dots$$

Note that here, we are fitting 12 parameters (one each for $s_1, \dots, s_d$) from n observations. If n is not that big, fitting 12 parameters might lead to overfitting.

4.0.3 Differencing

How can we obtain residuals adjusted for seasonality from the data without explicitly fitting a seasonality function? Recall that a function s is a periodic function of period d if $s_{t+d} = s_t$ for all t. The model that we have in mind here is: $X_t = s_t + Z_t$.

Clearly $X_t - X_{t-d} = s_t - s_{t-d} + Z_t - Z_{t-d} = Z_t - Z_{t-d}$. Therefore, the lag-$d$ differenced data $X_t - X_{t-d}$ do not display any seasonality. This method of producing deseasonalized residuals is called *Seasonal Differencing*.

5 Data Transformations

Suppose that the time series data set has a trend and that the variability increases along with the trend function. An example is the UKgas dataset in R. In such a situation, transform the data using the logarithm or a square root so that the resulting data look reasonably homoscedastic (having the same variance throughout).

Why log or square root? It helps to know a little bit about variance stabilizing transformations. Suppose X is a random variable having mean m. A *very heuristic* calculation gives an *approximate* answer for the variance of a function $f(X)$ of the random variable X? Expand $f(X)$ in its Taylor series up to *first order* around m:

$$f(X) \approx f(m) + f'(m)(X - m)$$

As a result,

$$\text{var}(f(X)) \approx \text{var}\left(f(m) + f'(m)(X - m)\right) = (f'(m))^2 \text{var}(X).$$

Thus if

1. $\text{var}(X) = Cm$ and $f(x) = \sqrt{x}$, we would get $\text{var}(X) \approx C/4$.
2. $\text{var}(X) = Cm^2$ and $f(x) = \log x$, we would get $\text{var}(X) \approx C$.

The key is to note that in both the above cases, the approximate variance of $f(X)$ does not depend on m anymore.

The above rough calculation suggests the following insight into time series data analysis. A model of the form $X_t = m_t + W_t$ where m_t is a *deterministic* function and W_t is purely random or stationary (next week) assumes that the variance of X_t does not vary with t. Suppose however that the time plot of the data shows that the variance of X_t increases with its mean m_t, say $\text{var}(X_t) \propto m_t$. Then the rough calculation suggests that $\text{var}(\sqrt{X_t})$ should be approximately constant (does not depend on t) and hence the model $m_t + W_t$ should be fit to the transformed data $\sqrt{X_t}$ instead of the original data X_t. Similarly, if $\text{var}(X_t) \propto m_t^2$, then $\text{var}(\log X_t)$ should be approximately constant.

Thus, if the data show increased variablity with a trend, then apply a transformation such as log or square root depending on whether the variability in the *resulting* data set is constant across time.

By the way, *count* data are usually modelled via Poisson random variables and the variance of a Poisson equals its mean. So one typically works with square roots while dealing with count (Poisson) data.

Box-Cox transformations: The square-root and the logarithm are special cases of the Box-Cox Transformations given by:

$$\begin{aligned} Y_t &= \frac{X_t^\lambda - 1}{\lambda} \qquad \text{if } \lambda \neq 0 \\ &= \log X_t \qquad \text{if } \lambda = 0. \end{aligned} \tag{2}$$

Square root essentially corresponds to $\lambda = 1/2$.

Reading: See relevant parts in Chapter 2 of the book.