

## Exercise Series 4

1. The dataset `bmw` is a time series of log returns of the BMW stock (business-daily, between June 1986 and March 1990). The log return is defined as follows:

$$X_t = \log \left( \frac{P_t}{P_{t-1}} \right),$$

where  $P_t$  is the stock price at time  $t$ . Log returns can be modelled by

$$X_t = \sigma_t \epsilon_t, \text{ where } \mathbf{E}[\epsilon_t] = 0, \text{Var}(\epsilon_t) = 1, \quad (1)$$

$\epsilon_t$  independent of  $\{X_s; s < t\}$ ,  $\sigma_t^2 = v(X_{t-1})$ , where  $v: \mathbb{R} \mapsto \mathbb{R}^+$  is the so-called “volatility function”. Thus,  $X_t$  depends on  $\{X_s; s < t\}$  only through  $X_{t-1}$  (Markov-property).

The model can be fitted by nonparametric regression of the function  $v$  in

$$Y_t = X_t^2 = v(X_{t-1}) + \eta_t, \text{ where } \eta_t = \sigma_t^2(\epsilon_t^2 - 1)$$

is treated as error term. The data can be downloaded at

<http://stat.ethz.ch/Teaching/Datasets/bmw.dat>

to a file with name `bmw.dat`, say, and read into **R** by

```
bmwlr <- scan("bmw.dat")
```

`bmwlr` should be a vector of 1000 observations.

- a) Compute  $\mathbf{E}[X_t | X_{t-1}, X_{t-2}, \dots]$ ,  $\text{Var}(X_t | X_{t-1}, X_{t-2}, \dots)$ ,  $\text{Cov}(X_t, X_{t-h})$ ,  $h > 0$ .

**Background about conditional expectations:**

For two (possibly multi-dimensional) random variables  $X$  and  $Y$ , the conditional distribution  $P^{Y|X=x}$  can be uniquely defined for  $P$ -almost all values of  $X$ . Define  $h(x) = \mathbf{E}[Y|X=x]$  as the expectation of  $Y$  under the conditional distribution  $P^{Y|X=x}$ . For the random variable  $X$ ,  $h(X) = \mathbf{E}[Y|X]$  is a random variable. Here is a very useful equation (the so-called tower property), which will be needed for parts a and b:

$$\mathbf{E}[Y] = \mathbf{E}[\mathbf{E}[Y|X]], \quad (2)$$

the outer expectation taken over the distribution of  $X$ . Conditional variances and covariances are defined analogously.

- b) Show  $\mathbf{E}[\eta_t] = 0$ .

**Note:** Other usual model assumptions on errors, such as independence, are not fulfilled by  $\eta_t$ , but with some effort (don't try!) it can be shown that  $v$  can be optimally estimated by the same estimation methods as if the  $\eta_t$  would be independent errors.

- c) Model (1) is often chosen for this kind of data because it leads to observations that are not autocorrelated<sup>1</sup> (as shown in part a), but dependent. Dependency can be verified by showing that under the model,  $\text{Cov}(X_t^2, X_{t-h}^2) \neq 0$ ,  $h > 0$  (complicated). Plot and interpret the autocorrelation functions of  $X_t$  and  $X_t^2$  for the BMW-dataset.

**R-hint:** Function `acf`. For example, “autocorrelation of lag 1” (in the plot, with 1000 observations, indicated as lag 1 out of 999) means correlation between  $X_t$  and  $X_{t-1}$ . The plot shows also an acceptance region (at 5%-significance level) for testing the null hypothesis of uncorrelated observations.

- d) Fit the data using the nonparametric regression methods Nadaraya-Watson, local polynomial and smoothing splines for the regression function  $v$ . Check model assumptions. Comment on the results and compare the fits obtained using the previously mentioned nonparametric estimators.

**R-hint:** There are numerous functions to perform nonparametric regression and here are some of them. Consider the help-pages for details.

<code>ksmooth</code>	<code>library(stats)</code>	Nadaraya-Watson kernel regression
<code>loess</code>	<code>library(stats)</code>	local polynomial
<code>smooth.spline</code>	<code>library(stats)</code>	smoothing splines
<code>locpoly</code>	<code>library(KernSmooth)</code>	local polynomial
<code>dpill</code>	<code>library(KernSmooth)</code>	optimal bandwidth estimation
<code>lokerns</code>	<code>library(lokern)</code>	kernel regression with local optimal bandwidth

Note that for computing residuals it is necessary to know the fitted values at the data points. For `ksmooth` they are provided via parameter `x.points` and for `loess` and `smooth.spline` via `fitted()`. For the other methods, a very dense grid has to be chosen and the nearest value in the grid could be used.

**Warning:** The structure in the data is pretty unclear. This is not a very didactic example.

**Preliminary discussion:** Friday, May 5, 2006.

**Deadline:** Friday, May 12, 2006, at the beginning of the seminar.

**Advice:** Every Thursday, 12.00-13.00, LEO C15, Leonhardstr. 27, or contact either Bernadetta Tarigan, [tarigan@stat.math.ethz.ch](mailto:tarigan@stat.math.ethz.ch), or Nicoleta Gosoniu, [gosoniu@ifspm.unizh.ch](mailto:gosoniu@ifspm.unizh.ch).

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<sup>1</sup>“Autocorrelated” refers to correlation over time, i.e., correlation between  $X_t$  and  $X_{t-h}$ ,  $h > 0$ .