

An Introduction to

*AD MODEL BUILDER Version 5.0.1*

For Use in Nonlinear Modeling and Statistics

*AD Model Builder*

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# Chapter 1

## Getting started with AD Model Builder

This manual describes AD Model Builder, the fastest, most powerful software for rapid development and fitting of general nonlinear statistical models available. The accompanying demonstration disk has a number of example programs from various fields including chemical engineering, natural resource modeling, and financial modeling. As you will see, with a few statements you can build powerful programs to solve problems that would completely defeat other modeling environments. The AD Model Builder environment makes it simple to deal with recurring difficulties in nonlinear modeling, such as restricting the values which parameters can assume, carrying out the optimization in a stepwise manner, and producing a report of the estimates of the standard deviations of the parameter estimates. And these techniques scale up to models with at least 1500 independent parameters on a 120 MH Pentium PC and more on more powerful platforms. So, if you are interested in a really powerful environment for nonlinear modeling – read on!

AD Model Builder provides a template-like approach to code generation. Instead of needing to write all the code for the model the user can employ any ASCII file editor to simply fill in the template, describing the particular aspects of the model – data, model parameters, and the fitting criterion to be used. With this approach the specification of the model is reduced to the absolute minimum number of statements. Reasonable default behaviour for various aspects of modeling such as the input of data and initial parameters and reporting of results are provided. Of course it is possible to override this default behaviour to customize an application when desired. The command line argument `-ind NAME` followed by the string `NAME` changes the default data input file to `NAME`.

The various concepts embodied in AD Model Builder are introduced in a series of examples. You should at least skim through each of the examples in the order they appear so that you will be familiar with the concepts used in the later examples. The examples disk contains the AD Model Builder template code, the C++ code produced by AD Model Builder and the executable programs produced by compiling the C++ code. This process of producing the executable is automated so that the user who doesn't wish to consider the vagaries of C++

programming can go from the AD Model Builder template to the compiled executable in one step. Assuming that the C++ compiler and AD Model Builder and AUTODIF libraries have been properly installed, then to produce a AD Model Builder executable it is only necessary to type `makeadm root` where `root.tpl` is the name of the ASCII file containing the template specification. To simplify model development two modes of operation are provided, a safe mode with bounds checking on all array objects and an optimized mode for fastest execution.

AD Model Builder achieves its high performance levels by employing the AUTODIF C++ class library. AUTODIF combines an array language with the reverse mode of Automatic differentiation supplemented with precompiled adjoint code for the derivatives of common array and matrix operations. However, all of this is completely transparent to the AD Model Builder user. It is only necessary to provide a simple description of the statistical model desired and the entire process of fitting the model to data and reporting the results is taken care of automatically.

Although C++ potentially provides good support for mathematical modeling, the language is rather complex – it cannot be learned in a few days. Moreover many features of the language are not needed for mathematical modeling. A novice user who wishes to build mathematical models may have a difficult time deciding which features of the language to learn and which features can be ignored until later. AD Model Builder is intended to help overcome these difficulties and to speed up model development. When using AD Model Builder most of the aspects of C++ programming are hidden from the user. In fact the beginning user can be almost unaware that C++ underlies the implementation of AD Model Builder. It is only necessary to be familiar with some of the simpler aspects of C or C++ syntax.

To interpret the results of the statistical analysis AD Model Builder provides simple methods for calculating the profile likelihood and Markov chain simulation estimates of the posterior distribution for parameters of interest (Hastings-Metropolis algorithm).

A short description of each example follows.

A very simple example. This is a trivial least squares linear model included simply to introduce the basics of AD Model Builder.

A simple nonlinear regression model for estimating the parameters describing a von Bertalanffy growth curve from size-at-age data. AD Model Builder's robust regression routine is introduced and used to illustrate how problems caused by "outliers" in the data can be avoided.

A chemical kinetics problem. A model defined by a system of ordinary differential equations. The purpose is to estimate the parameters which describe the chemical reaction.

A problem in financial modeling. A Generalized Autoregressive Conditional Heteroskedasticity or GARCH model is used to attempt to describe the time series of returns from some market instrument.

A problem in natural resource management. The Schaeffer-Pella-Tomlinson Model for investigating the response of an exploited fish population is developed and extended to

include a Bayesian times series treatment of time-varying carrying capacity. This example is interesting because the model is rather tempermental and several techniques for producing reliable convergence of the estimation procedure to the correct answer are described. For one of the data sets over 100 parameters are estimated.

A Simple Fisheries catch-at-age model. These models are used to try and estimate the exploitation rates etc. in exploited fish populations.

More complex examples are presented in subsequent chapters.

An AD Model Builder template consists of up to nine sections. Six of these sections are optional. Optional sections are enclosed in brackets [ ]. The optional FUNCTION keyword defines a subsection of the PROCEDURE\_SECTION.

```
DATA_SECTION

[INITIALIZATION_SECTION]

PARAMETER_SECTION

[PRELIMINARY_CALCS_SECTION]

PROCEDURE_SECTION

[FUNCTION]

[REPORT_SECTION]

[RUNTIME_SECTION]

[TOP_OF_MAIN_SECTION]

[GLOBALS_SECTION]

[BETWEEN_PHASES_SECTION]

[FINAL_SECTION]
```

The simplest model contains only the three required sections, a DATA\_SECTION, a PARAMETER\_SECTION, and a PROCEDURE\_SECTION.

## Example 1 – linear least-squares

To illustrate the method we begin with a simple statistical model which is to estimate the parameters of a linear relationship of the form

$$Y_i = ax_i + b \quad \text{for } 1 \leq i \leq n$$

where  $x_i$  and  $Y_i$  are vectors, and  $a$  and  $b$  are the model parameters which are to be estimated. The parameters are estimated by the method of least-squares that is we find the values of  $a$  and  $b$  so that the sum of the squared differences between the observed values  $Y_i$  and the predicted values  $ax_i + b$  is minimized. That is we want to solve the problem

$$\min_{a,b} \sum_{i=1}^n (Y_i - ax_i - b)^2$$

The template for this model is in the file `SIMPLE.TPL`. To make the model one would type `makeadm simple`. The resulting executable for the model is in the file `SIMPLE.EXE`. The contents of `SIMPLE.TPL` are. (Anything following `//` is a comment.)

```
DATA_SECTION
  init_int nobs           // nobs is the number of observations
  init_vector Y(1,nobs)  // the observed Y values
  init_vector x(1,nobs)
PARAMETER_SECTION
  init_number a
  init_number b
  vector pred_Y(1,nobs)
  objective_function_value f
PROCEDURE_SECTION
  pred_Y=a*x+b;          // calculate the predicted Y values
  f=regression(Y,pred_Y); // do the regression -- the vector of
                          // observations goes first
```

The main requirement is that all keywords must begin in column 1 while the code itself must be indented.

## The DATA SECTION

Roughly speaking, the data consist of the stuff in the real world which you observe and want to analyze. The data section describes the structure of the data in your model. Data objects consist of integers (`int`) and floating point numbers(`number`), and these can be grouped into one dimensional (`ivector` and `vector`) and two dimensional (`imatrix` and `matrix`) arrays. The “i” in `ivector` distinguishes a vector of type `int` from a vector of type `number`. For arrays of type `number` there are currently arrays up to dimension 7.

Some of your data must be read in from somewhere, that is, you need to start with something. These data objects are referred to as initial objects and are distinguished by the prefix `init`, such as `init_int` or `init_number`. All objects prefaced with `init` in the `DATA_SECTION` are read in from a data file in the order in which they are declared. The default file names for various files are derived from the name of the executable program. If the executable file is named `ROOT.EXE` then the default input data file name is `ROOT.DAT`. For this example the executable file is named `SIMPLE.EXE` so the default data file is `SIMPLE.DAT`. Notice that once an object has been read in, its value is available to be used to describe other

data objects. In this case the value of `nobs` can be used to define the size of the vectors `Y` and `x`. The next line `init_vector Y(1,nobs)` defines an initial vector object `Y` whose minimum valid index is 1, and whose maximum valid index is `nobs`. This vector object will be read in next from the data file. The contents of the file `SIMPLE.DAT` are shown below.

```
# number of observations
  10
# observed Y values
  1.4  4.7  5.1  8.3  9.0  14.5  14.0  13.4  19.2  18
# observed x values
  -1  0  1  2  3  4  5  6  7  8
```

It is possible to put comment lines in the data files. Comment lines must have the character `#` in the first column.

It is often useful to have data objects which are not initial. Such objects have their values calculated from the values of initial data objects. Examples of the use of non initial data objects are given below.

## The Parameter Section

It is the parameters of your model which provide the analysis of the data (or perhaps more correctly is the values of these parameters as picked by the fitting criterion for the model which provide the analysis of the data). The `PARAMETER_SECTION` is used to describe the structure of the parameters in your model. The description of the model parameters is similar to that used for the data in the `DATA_SECTION`.

All parameters are floating point numbers (or arrays of floating point numbers.) The statement `init_number b` defines a floating point number (actually a double). The preface `init` means that this is an initial parameter. Initial parameters have two properties which distinguish them from other model parameters. First, all of the other model parameters are calculated from the initial parameters. This means that in order to calculate the values of the model parameters it is first necessary to have values for the initial parameters. A major difference between initial data objects (which must be read in from a data file) and initial parameters is that since parameters are estimated in the model it is possible to assign initial default values to them.

The default file name for the file which contains initial values for the initial model parameters is `ROOT.PIN`. If no file named `ROOT.PIN` is found, default values are supplied for the initial parameters. (Methods for changing the default values for initial parameters are described below.) The statement `vector pred_Y(1,nobs)` defines a vector of parameters. Since it is not prefaced with `init` the values for this vector will not be read in from a file or given default values. It is expected that the value of the elements of this vector will be calculated in terms of other parameters.

The statement `objective_function_value f` defines a floating point number (again actually a double). It will hold the value of the fitting criterion. The parameters of the

model are chosen so that this value is minimized<sup>1</sup>. Every AD Model Builder template must include a declaration of an object of type `objective_function_value` and this object must be set equal to a fitting criterion. (Don't worry, for many models the fitting criterion is provided for you as in the `regression` and `robust_regression` fitting criterion functions in the current and next examples.

## The Procedure Section

The `PROCEDURE_SECTION` contains the actual model calculations. This section contains C++ code and C++ syntax must be obeyed. (Those familiar with C or C++ will notice that the usual methods for defining and ending a function are not necessary and in fact can not be used for the routine in the main part of this section.)

Statements must end with a ";" exactly as with C or C++. The ";" is optional in the `DATA_SECTION` and the `PARAMETER_SECTION`. The code uses AUTODIF's vector operations which enable you to avoid writing a lot of code for loops. In the statement `pred_Y=a*x+b;` the symbol `a*x` forms the product of the number `a` and the components of the vector `x` while `+b` adds the value of the number `b` to this product so that `pred_Y` has the components  $ax_i + b$ . In the line `f=regression(Y,pred_Y);` the function `regression` calculates the log-likelihood function for the regression and assigns this value to the object `f` which is of type `objective_function_value`. This code generalizes immediately to nonlinear regression models and can be trivially modified (with the addition of one word) to perform the robust nonlinear regression discussed in the second example. For the reader who want to know, the form of the regression function is described in the Appendix.

Note that the vector of observed values goes first. The use of the `regression` function makes the purpose of the calculations clearer, and it prepares the way for modifying the routine to use AD Model Builder's robust regression function.

## The Preliminary Calcs Section

NOTE: The use of `LOCAL_CALCS` and its variants in the `DATA_SECTION` and the `PROCEDURE_SECTION` has greatly reduced the need for the `PRELIMINARY_CALCS_SECTION`.

The `PRELIMINARY_CALCS_SECTION` as its name implies permits one to do preliminary calculations with the data before getting into the model proper. Often the input data are not in a convenient form for doing the analysis and one wants to carry out some calculations with the input data to put them in a more convenient form. Suppose that the input data for the simple regression model are in the form

```
# number of observations
```

---

<sup>1</sup>Thus it should be set equal to minus the log-likelihood function if that criterion is used

```

10
# observed Y values  observed x values
1.4                -1
4.7                0
5.1                1
8.3                2
9.0                3
14.5               4
14.0               5
13.4               6
19.2               7
18                 8

```

The problem is that the data are in pairs in the form  $(Y_i, x_i)$ , so that we can't read in either the  $x_i$  or  $Y_i$  first. To read in the data in this format we will define a matrix with `nobs` rows and 2 columns. The `DATA_SECTION` becomes

```

DATA_SECTION
  init_int nobs
  init_matrix Obs(1,nobs,1,2)
  vector Y(1,nobs)
  vector x(1,nobs)

```

Notice that since we do not want to read in `Y` or `x` these objects are no longer initial objects, that is their declarations are no longer prefaced with `int`. The observations will be read into the initial matrix object `Obs` so that `Y` is in the first column of `Obs` while `x` is in the second column. If we don't want to change the rest of the code the next problem is to get the first column of `Obs` into `Y` and the second column of `Obs` into `x`. The following code in the `PRELIMINARY_CALC_SECTION` will accomplish this objective. It uses the function `column` which extracts a column from a matrix object so that it can be put into a vector object.

```

PRELIMINARY_CALC_SECTION
  Y=column(Obs,1); // extract the first column
  x=column(Obs,2); // extract the second column

```

## The use of loops and element-wise operations

This section can be skipped on first reading.

To accomplish the column-wise extraction presented above you would have to know that AUTODIF provides the `column` operation. What if you didn't know that and don't feel like reading the manual yet? For those who are familiar with C it is generally possible to use lower level "C-like" operations to accomplish the same objective as AUTODIF's array and matrix operations. In this case the columns of the matrix `Obs` can also be copied to the vectors `x` and `Y` by using a standard `for` loop and the following element-wise operations

```

PRELIMINARY_CALC_SECTION
  for (int i=1;i<=nobs;i++)
  {
    Y[i]=Obs[i][1];

```

```

    x[i]=Obs[i][2];
}

```

Incidentally, the C-like operation [] was used for indexing members of arrays. AD Model Builder also supports the use of () so that the above code could be written as

```

PRELIMINARY_CALCS_SECTION
  for (int i=1;i<=nobs;i++)
  {
    Y(i)=Obs(i,1);
    x(i)=Obs(i,2);
  }

```

which may be more readable for some users. Notice that it is also possible to define C objects like the object of type int i used as the index for the for loop “on the fly” in the PRELIMINARY\_CALCS\_SECTION or the PROCEDURE\_SECTION.

## The default output from AD Model Builder

By default AD Model Builder produces three or more files ROOT.PAR which contains the parameter estimates in ASCII format, ROOT.BAR which is the parameter estimates in a binary file format, and ROOT.COR which contains the estimated standard deviations and correlations of the parameter estimates. The template code for the simple model is in the file file SIMPLE.TPL. The input data is in the file SIMPLE.DAT. The parameter estimates are in the file SIMPLE.PAR. By default the standard deviations and the correlation matrix for the model parameters are estimated. They are in the file SIMPLE.COR

index		value	std dev	1	2
1	a	1.9091e+00	1.5547e-01	1	
2	b	4.0782e+00	7.0394e-01	-0.773	1

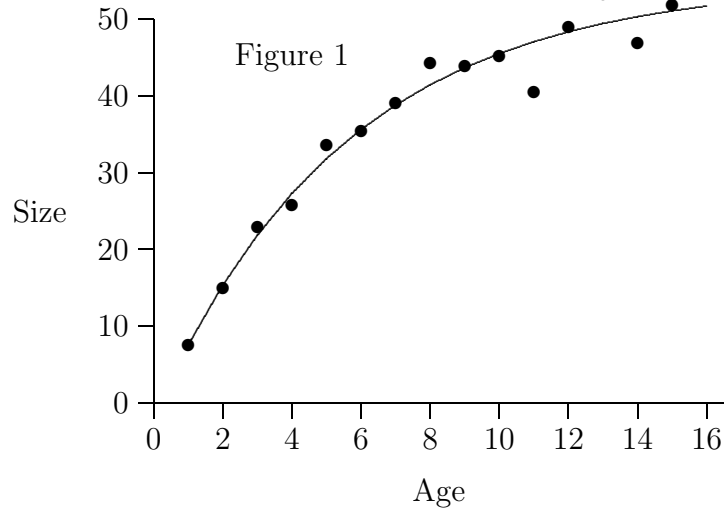
The format of the standard deviations report is to give the name of the parameter followed by its value and standard deviation. After that the correlation matrix for the parameters is given.

## Robust Nonlinear regression with AD Model Builder

The code for the admodel template for this example is found in the file VONB.TPL. This example is intended to demonstrate the advantages of using AD Model Builder’s robust regression routine over standard nonlinear least square regression procedures. Further discussion about the underlying theory can be found in the AUTODIF User’s Man-



ual, but it is not necessary to understand the theory to make use of the procedure.



Results for nonlinear regression with good data set

index		value	std dev	1	2	3
1	Linf	5.4861e+01	2.4704e+00	1.0000		
2	K	1.7985e-01	2.7127e-02	-0.9191	1.0000	
3	t0	1.8031e-01	2.9549e-01	-0.5856	0.7821	1.0000

This example estimates the parameters describing a growth curve from a set of data consisting of ages and size-at-age data. The form of the (von Bertalanffy) growth curve is assumed to be

$$s(a) = L_{\infty}(1 - \exp(-K(a - t_0))) \quad (1.1)$$

The three parameters of the curve to be estimated are  $L_{\infty}$ ,  $K$ , and  $t_0$ .

Let  $O_i$  and  $a_i$  be the observed size and age of the  $i$ 'th animal. The predicted size  $s(a_i)$  is given by equation 1.1. The least squares estimates for the parameters are found by minimizing

$$\min_{L_{\infty}, K, t_0} \sum_i (O_i - s(a_i))^2$$

```

DATA_SECTION
  init_int nobs;
  init_matrix data(1,nobs,1,2)
  vector age(1,nobs);
  vector size(1,nobs);
PARAMETER_SECTION
  init_number Linf;
  init_number K;
  init_number t0;
  vector pred_size(1,nobs)

```

```

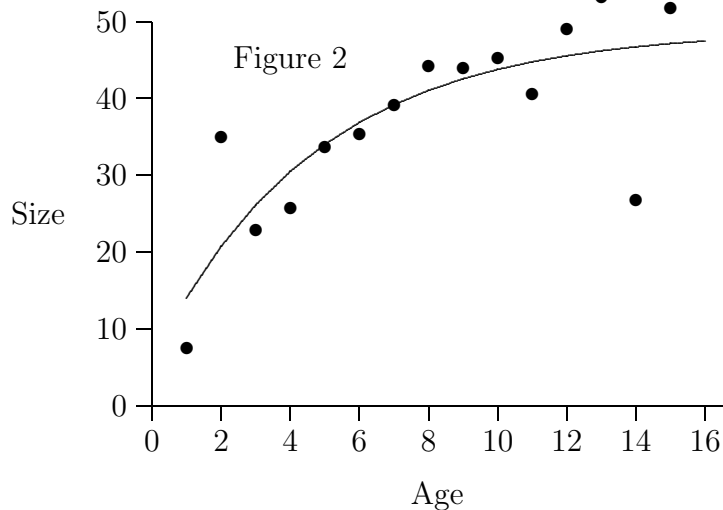
    objective_function_value f;
PRELIMINARY_CALC_SECTION
    // get the data out of the columns of the data matrix
    age=column(data,1);
    size=column(data,2);
    Linf=1.1*max(size); // set Linf to 1.1 times the longest observed length
PROCEDURE_SECTION
    pred_size=Linf*(1.-exp(-K*(age-t0)));
    f=regression(size,pred_size);

```

Notice the use of the `regression` function which calculates the log-likelihood function of the nonlinear least-squares regression. This part of the code is formally identical to the code for the linear regression problem in the simple example even though we are now doing nonlinear regression. A graph of the least-square estimated growth curve and the observed data is given in figure 1. The parameter estimates and their estimated standard deviations which are produced by AD Model Builder are also given. For example the estimate for  $L_\infty$  is 54.86 with a standard deviation of 2.47. Since a 95% confidence limit is about  $\pm$  two standard deviations the usual 95% confidence limit of  $L_\infty$  for this analysis would be  $54.86 \pm 4.94$ .

A disadvantage of least squares regression is the sensitivity of the estimates to a few “bad” data points or outliers. Figure 2 show the least squares estimates when the observed size for age 2 and age 14 have been moved off the curve. There has been a rather large change in some of the parameter estimates. For example the estimate for  $L_\infty$  has changed from 54.86 to 48.91 and the estimated standard deviation for this parameter has increased to 5.99. This is a common effect of outliers on least-squares estimates. They greatly increase the size of the estimates of the standard deviations. As a result the confidence limits for the parameters are increased. In this case the 95% confidence limits for  $L_\infty$  have been increased from  $54.86 \pm 4.94$  to  $48.91 \pm 11.98$ .

Of course for this simple example it could be argued that a visual examination of the residuals would identify the outliers so that they could be removed. This is true, but in larger nonlinear models it is often not possible or convenient to identify and remove all the outliers in this fashion. Also the process of removing “inconvenient” observations from data can be uncomfortably close to “cooking” the data in order to obtain the desired result from the analysis. An alternative approach which avoids these difficulties is to employ AD Model Builder’s robust regression procedure which removes the undue influence of outlying points without the need to expressly remove them from the data.



Nonlinear regression with bad data set

```
Nonlinear regression with bad data set
index      value      std dev      1      2      3
  1  Linf  4.8905e+01  5.9938e+00  1.0000
  2   K    2.1246e-01  1.2076e-01 -0.8923  1.0000
  3  t0   -5.9153e-01  1.4006e+00 -0.6548  0.8707  1.0000
```

## Modifying the model to use robust nonlinear regression

To invoke the robust regression procedure it is necessary to make three changes to the existing code. The template for the robust regression version of the model can be found in the file VONBR.TPL.

```
DATA_SECTION
  init_int nobs;
  init_matrix data(1,nobs,1,2)
  vector age(1,nobs)
  vector size(1,nobs)
PARAMETER_SECTION
  init_number Linf
  init_number K
  init_number t0
  vector pred_size(1,nobs)
  objective_function_value f
  init_bounded_number a(0.0,0.7,2)
PRELIMINARY_CALCS_SECTION
  // get the data out of the columns of the data matrix
  age=column(data,1);
  size=column(data,2);
  Linf=1.1*max(size); // set Linf to 1.1 times the longest observed length
  a=0.7;
```

```

PROCEDURE_SECTION
  pred_size=Linf*(1.-exp(-K*(age-t0)));
  f=robust_regression(size,pred_size,a);

```

The main modification to the model involves the addition of the parameter `a`, which is used to estimate the amount of contamination by outliers. This parameter is declared in the `PARAMETER_SECTION`.

```

init_bounded_number a(0.0,0.7,2)

```

This introduces two concepts, putting bounds on the values which initial parameters can take on and carrying out the minimization in a number of stages. The value of `a` should be restricted to lie between 0.0 and 0.7 (See the discussion on robust regression in the AUTODIF user's manual if you want to know where the 0.0 and 0.7 come from). This is accomplished by declaring `a` to be of type `init_bounded_number`. In general it is not possible to estimate the parameter `a` determining the amount of contamination by outliers until the other parameters of the model have been "almost" estimated, that is, until we have done a preliminary fit of the model. This is a common situation in nonlinear modeling and is discussed further in some later examples. So we want to carry out the minimization in two phases. During the first phase `a` should be held constant. In general for any initial parameter the last number in its declaration, if present, determines the number of the phase in which that parameter becomes active. If no number is given the parameter becomes active in phase 1. (Note: For an `init_bounded_number` the upper and lower bounds must be given so the declaration

```

init_bounded_number a(0.0,0.7)

```

would use the default phase 1. The 2 in the declaration for `a` causes `a` to be constant until the second phase of the minimization. The second change to the model involves the default initial value `a`. The default value for a bounded number is the average of the upper and lower bounds. For `a` this would be 0.35 which is too small. We want to use the upper bound of 0.7. This is done by adding the line

```

a=0.7;

```

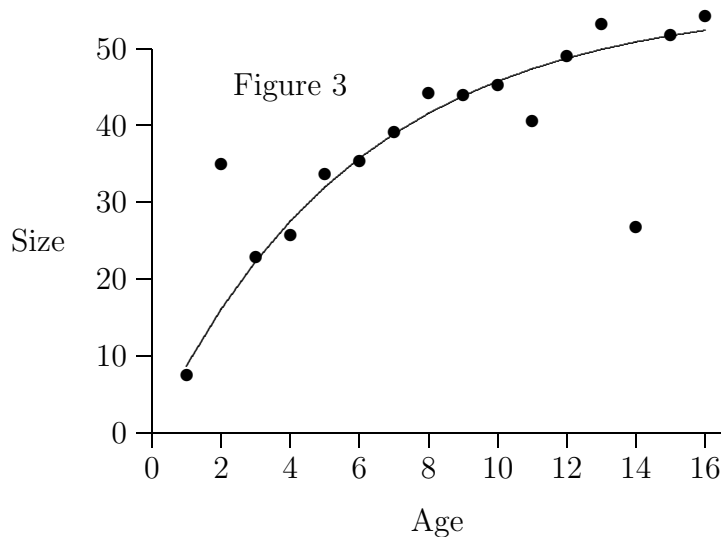
in the `PRELIMINARY_CALC_SECTION`. Finally we modify the statement in the `PROCEDURE_SECTION` including the regression function to

```

f=robust_regression(size,pred_size,a);

```

to invoke the robust regression function. That's all there is to it! These three changes will convert any AD Model builder template from a nonlinear regression model to a robust nonlinear regression model.

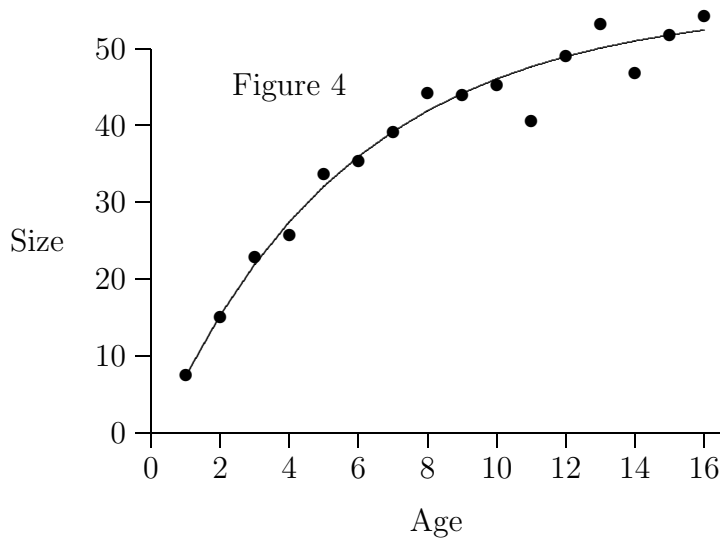


#### Robust Nonlinear regression with bad data set

index		value	std dev	1	2	3	4
1	Linf	5.6184e+01	3.6796e+00	1.0000			
2	K	1.6818e-01	3.4527e-02	-0.9173	1.0000		
3	t0	6.5129e-04	4.5620e-01	-0.5483	0.7724	1.0000	
4	a	3.6144e-01	1.0721e-01	-0.1946	0.0367	-0.2095	1.0000

The results for the robust regression fit to the bad data set are shown in figure 3. The estimate for  $L_\infty$  is 56.18 with a standard deviation of 3.68 to give a 95% confidence interval of about  $56.18 \pm 7.36$ . Both the parameter estimates and the confidence limits are much less affected by the outliers for the robust regression estimates than they are for the least squares estimates. The parameter a is estimated to be equal to 0.36 which indicates that the robust procedure has detected some moderately large outliers.

The results for the robust regression fit to the good data set are shown in figure 4. The estimates are almost identical to the least-square estimates for the same data. This is a property of the robust estimates. They do almost as well as the least-square estimates when the assumption of normally distributed errors in the statistical model is satisfied exactly, and they do much better than least square estimates in the presence of moderate or large outliers. You can lose only a little and you stand to gain a lot by using these estimators.



Robust Nonlinear regression with good data set

index		value	std dev	1	2	3	4
1	Linf	5.5707e+01	1.9178e+00	1.0000			
2	K	1.7896e-01	1.9697e-02	-0.9148	1.0000		
3	t0	2.1490e-01	2.0931e-01	-0.5604	0.7680	1.0000	
4	a	7.0000e-01	3.2246e-05	-0.0001	0.0000	-0.0000	1.0000

## Chemical engineering – a chemical kinetics problem

This example may strike you as being fairly complicated. If so, you should compare it with the original solution using the so-called sensitivity equations. The reference is Bard, *Nonlinear Parameter Estimation*, chapter 8. We consider the chemical kinetics problem introduced on page 233. This is a model defined by a first order system of two ordinary differential equations.

$$\begin{aligned}
 ds_1/dt &= -\theta_1 \exp(-\theta_2/T)(s_1 - e^{-1000/T}s_2^2)/(1 + \theta_3 \exp(-\theta_4/T)s_1)^2 \\
 ds_2/dt &= 2\theta_1 \exp(-\theta_2/T)(s_1 - e^{-1000/T}s_2^2)/(1 + \theta_3 \exp(-\theta_4/T)s_1)^2
 \end{aligned}
 \tag{1.2}$$

The differential equations describe the evolution over time of the concentrations of the two reactants,  $s_1$ , and  $s_2$ . There are ten initial parameters in the model,  $\theta_1, \dots, \theta_{10}$ .  $T$  is the temperature at which the reaction takes place. To integrate the system of differential equations we require the initial concentrations of the reactants,  $s_1(0)$  and  $s_2(0)$  at time 0.

The reaction was carried out three times at temperatures of 200, 400, and 600 degrees. For the first run there were initially equal concentrations of the two reactants. The second run initially consisted of only the first reactant, and the third run initially consisted of only the second reactant. The initial concentrations of the reactants are known only approximately. They are

Run 1	$s_1(0) = \theta_5 = 1 \pm 0.05$	$s_2(0) = \theta_6 = 1 \pm 0.05$
Run 2	$s_1(0) = \theta_7 = 1 \pm 0.05$	$s_2(0) = 0$
Run 3	$s_1(0) = 0$	$s_2(0) = \theta_8 = 1 \pm 0.05$

The unknown initial concentrations are treated as parameters to be estimated with Bayesian prior distributions on them reflecting the level of certainty of their true values which we have. The concentrations of the reactants were not measured directly. Rather the mixture was analyzed by a “densitometer” whose response to the concentrations of the reactants is

$$y = 1 + \theta_9 s_1 + \theta_{10} s_2$$

where  $\theta_9 = 1 \pm 0.05$  and  $\theta_{10} = 2 \pm 0.05$ . The differences between the predicted and observed responses of the densitometer are assumed to be normally distributed so that least squares is used to fit the model. Bard employs an “explicit” method for integrating these differential equations, that is, the equations are approximated by a finite difference scheme like

$$\begin{aligned}
 s_1(t_{n+1}) &= s_1(t_n) \\
 &\quad -h \theta_1 \exp(-\theta_2/T)(s_1(t_n) - e^{-1000/T} s_2(t_n)^2)/(1 + \theta_3 \exp(-\theta_4/T)s_1(t_n))^2 \\
 s_2(t_{n+1}) &= s_2(t_n) \\
 &\quad + 2h \theta_1 \exp(-\theta_2/T)(s_1(t_n) - e^{-1000/T} s_2(t_n)^2)/(1 + \theta_3 \exp(-\theta_4/T)s_1(t_n))^2
 \end{aligned}
 \tag{1.3}$$

over the time period  $t_n$  to  $t_{n+1}$  of length  $h$ . Equations 2 are called explicit because the values of  $s_1$  and  $s_2$  at time  $t_{n+1}$  are given explicitly in terms of the values of  $s_1$  and  $s_2$  at time  $t_n$ .

The advantage of using an explicit scheme for integrating the model differential equations is that the derivatives of the model functions with respect to the model parameters also satisfy differential equations – called sensitivity equations (Bard pg 227-229). It is possible to integrate these equations as well as the model equations to get values for the derivatives. However this involves generating a lot of extra code as well as carrying out a lot of extra calculations. Since with AD Model Builder it is not necessary to produce any code for derivative calculations it is possible to employ alternate schemes for integrating the differential equations.

Let  $A = \theta_1 \exp(-\theta_2/T)$ ,  $B = \exp(-1000/T)$ , and  $C = (1 + \theta_3 \exp(-\theta_4/T)s_1)^2$  In terms of  $A$  and  $C$  we can replace explicit finite difference scheme by the semi-implicit scheme

$$\begin{aligned}
 s_1(t_{n+1}) &= s_1(t_n) - hA(s_1(t_{n+1}) - Bs_2^2(t_{n+1}))/C \\
 s_2(t_{n+1}) &= s_2(t_n) + 2hA(s_1(t_{n+1}) - Bs_2(t_n)s_2(t_{n+1}))/C
 \end{aligned}
 \tag{1.4}$$

Now let  $D = hA/C$  and solve equations (3) for  $s_1(t_{n+1})$  and  $s_2(t_{n+1})$  to obtain

$$\begin{aligned} s_1(t_{n+1}) &= (s_1(t_n) + DBs_2(t_n))/(1 + D) \\ s_2(t_{n+1}) &= (s_2(t_n) + 2Ds_1(t_n))/(1 + (2DBs_2(t_n))) \end{aligned} \quad (1.5)$$

Implicit and semi-implicit schemes tend to be more stable than explicit schemes over large time steps and large values of some of the model parameters. This stability is especially important when fitting nonlinear models because the algorithms for function minimization will pick very large or “bad” values of the parameters from time to time and the minimization procedure will generally perform better when a more stable scheme is employed.

```

DATA_SECTION
  init_matrix Data(1,10,1,3)
  init_vector T(1,3) // the initial temperatures for the three runs
  init_vector stepsize(1,3) // the stepsize to use for numerical integration
  matrix data(1,3,1,10)
  matrix sample_times(1,3,1,10) // times at which reaction was sampled
  vector x0(1,3) // the beginning time for each of the three
                // runs
  vector x1(1,3) // the ending time for each of the three runs
                // for each of the three runs

PARAMETER_SECTION
  init_vector theta(1,10) // the model parameters
  matrix init_conc(1,3,1,2) // the initial concentrations of the two
                            // reactants over three time periods
  vector instrument(1,2) // determines the response of the densitometer
  matrix y_samples(1,10,1,2) // the predicted concentrations of the two
                             // reactants at the ten sampling periods
                             // obtained by integrating the differential
                             // equations
  vector diff(1,10) // the difference between the observed and
                   // readings of the densitometer
  objective_function_value f // the log_likelihood function
  number bayes_part // the Bayesian contribution
  number y2
  number x_n
  vector y_n(1,2)
  vector y_n1(1,2)
  number A // A B C D hold some common subexpressions
  number B
  number C
  number D

PRELIMINARY_CALCS_SECTION
  data=trans(Data); // it is more convenient to work with the transformed
                  // matrix

PROCEDURE_SECTION

  // set up the begining and ending times for the three runs
  x0(1)=0;
  x1(1)=90;
  x0(2)=0;
  x1(2)=18;
  x0(3)=0;
  x1(3)=4.5;

```



```

// set up the sample times for each of the three runs
sample_times(1).fill_seqadd(0,10); // fill with 0,10,20,...,90
sample_times(2).fill_seqadd(0,2); // fill with 0,2,4,...,18
sample_times(3).fill_seqadd(0,0.5); // fill with 0,0.5,1.0,...,4.5

// set up the initial concentrations of the two reactants for
// each of the three runs
init_conc(1,1)=theta(5);
init_conc(1,2)=theta(6);
init_conc(2,1)=theta(7);
init_conc(2,2)=0.0; // the initial concentrations is known to be 0
init_conc(3,1)=0.0; // the initial concentrations is known to be 0
init_conc(3,2)=theta(8);

// coefficients which determine the response of the densitometer
instrument(1)=theta(9);
instrument(2)=theta(10);
f=0.0;
for (int run=1;run<=3;run++)
{
    // integrate the differential equations to get the predicted
    // values for the y_samples
    int nstep=(x1(run)-x0(run))/stepsize(run);
    nstep++;
    double h=(x1(run)-x0(run))/nstep; // h is the stepsize for integration

    int is=1;
    // get the initial conditions for this run
    x_n=x0(run);
    y_n=init_conc(run);
    for (int i=1;i<=nstep+1;i++)
    {
        // gather common subexpressions
        y2=y_n(2)*y_n(2);
        A=theta(1)*exp(-theta(2)/T(run));
        B=exp(-1000/T(run));
        C=(1+theta(3)*exp(-theta(4)/T(run))*y_n(1));
        C=C*C;
        D=h*A/C;
        // get the y vector for the next time step
        y_n1(1)=(y_n(1)+D*B*y2)/(1.+D);
        y_n1(2)=(y_n(2)+2.*D*y_n(1))/(1.+(2*D*B*y_n(2)));

        // if an observation occurred during this time period save
        // the predicted value
        if (is <=10)
        {
            if (x_n<=sample_times(run,is) && x_n+h >= sample_times(run,is))
            {
                y_samples(is++)=y_n;
            }
        }
        x_n+=h; // increment the time step
        y_n=y_n1; // update the y vector for the next step
    }
    diff=(1.0+y_samples*instrument)-data(run); //differences between the
        // predicted and observed values of the densitometer
}

```

```

    f+=diff*diff; // sum of squared differences
}
// take the log of f and multiply by nobs/2 to get log-likelihood
f=15.*log(f); // This is (number of obs)/2. It is wrong in Bard (pg 236).

// Add the Bayesian stuff
bayes_part=0.0;
for (int i=5;i<=9;i++)
{
    bayes_part+=(theta(i)-1)*(theta(i)-1);
}
bayes_part+=(theta(10)-2)*(theta(10)-2);
f+=1./(2.*.05*.05)*bayes_part;

```

AD Model Builder produces a report containing values, standard deviations, and correlation matrix of the parameter estimates. As discussed below any parameter or group of parameters can easily be included in this report. For models with a large number of parameters this report can be a bit unwieldy so options are provided to exclude parameters from the report if desired.

index	value	std dev	1	2	3	4	5	6	7	8	9	10	
1	theta	1.37e+00	2.09e-01	1									
2	theta	1.12e+03	7.70e+01	0.95	1								
3	theta	1.80e+00	7.95e-01	0.9	0.98	1							
4	theta	3.58e+02	1.94e+02	0.91	0.98	0.99	1						
5	theta	1.00e+00	4.49e-02	0.20	0.28	0.12	0.17	1					
6	theta	9.94e-01	2.99e-02	-0.42	-0.35	-0.25	-0.22	-0.58	1				
7	theta	9.86e-01	2.59e-02	0.01	0.22	0.22	0.28	0.26	0.42	1			
8	theta	1.02e+00	1.69e-02	-0.38	-0.34	-0.36	-0.30	0.09	0.63	0.34	1		
9	theta	1.00e+00	2.59e-02	-0.02	-0.23	-0.23	-0.30	-0.28	-0.43	-0.98	-0.37	1	
10	theta	1.97e+00	3.23e-02	0.44	0.37	0.40	0.32	-0.09	-0.65	-0.37	-0.93	0.40	1

## Financial Modelling – A Generalized Autoregressive Conditional Heteroskedasticity or GARCH model

Time series models are often used in financial modeling. For these models the parameters are often extremely badly determined. With the stable numerical environment produced by AD Model Builder it is a simple matter to fit such models.

Consider a time series of returns  $r_t$  where  $t = 0, \dots, T$ , which are available from some type of financial instrument. The model assumptions are

$$r_t = \mu + \epsilon_t \quad h_t = a_0 + a_1 \epsilon_{t-1}^2 + a_2 h_{t-1} \quad \text{for } 1 \leq t \leq T, \quad a_0 \geq 0, \quad a_1 \geq 0, \quad a_2 \geq 0$$

where the  $\epsilon_t$  are independent normally distributed random variables with mean 0 and variance  $h_t$ . We assume  $\epsilon_0 = 0$  and  $h_0 = \sum_{i=0}^T (r_i - \bar{r})^2 / (T + 1)$ . There are four initial parameters to be estimated for this model,  $\mu$ ,  $a_0$ ,  $a_1$ , and  $a_2$ . The log-likelihood function for the vector  $r_t$  is equal to a constant plus

$$-.5 \sum_{t=1}^T (\log(h_t) + (r_t - \mu)^2 / h_t)$$

```

DATA_SECTION
  init_int T
  init_vector r(0,T)
  vector sub_r(1,T)
  number h0
INITIALIZATION_SECTION
  a0 .1
  a1 .1
  a2 .1
PARAMETER_SECTION
  init_bounded_number a0(0.0,1.0)
  init_bounded_number a1(0.0,1.0,2)
  init_bounded_number a2(0.0,1.0,3)
  init_number Mean
  vector eps2(1,T)
  vector h(1,T)
  objective_function_value log_likelihood
PRELIMINARY_CALCS_SECTION
  h0=square(std_dev(r)); // square forms the element-wise square
  sub_r=r(1,T); // form a subvector so we can use vector operations
  Mean=mean(r); // calculate the mean of the vector r
PROCEDURE_SECTION
  eps2=square(sub_r-Mean);
  h(1)=a0+a2*h0;
  for (int t=2;t<=T;t++)
  {
    h(t)=a0+a1*eps2(t-1)+a2*h(t-1);
  }
  // calculate minus the log-likelihood function
  log_likelihood=.5*sum(log(h)+elem_div(eps2,h)); // elem_div performs
  // element-wise division of vectors
RUNTIME_SECTION
  convergence_criteria .1, .1, .001
  maximum_function_evaluations 20, 20, 1000

```

We have used vector operations such as `elem_div` and `sum` to simplify the code. Of course the code could also have employed loops and element-wise operations. The parameter values and standard deviation report for this model appears below.

index		value	std dev	1	2	3	4
1	a0	1.6034e-04	2.3652e-05	1.0000			
2	a1	9.3980e-02	2.0287e-02	0.1415	1.0000		
3	a2	3.7263e-01	8.2333e-02	-0.9640	-0.3309	1.0000	
4	Mean	-1.7807e-04	3.0308e-04	0.0216	-0.1626	0.0144	1.0000

This example employs bounded initial parameters. Often it is necessary to put bounds on parameters in nonlinear modeling to ensure that the minimization is stable. In this example  $a_0$  is constrained to lie between 0.0 and 1.0

```
init_bounded_number a0(0.0,1.0)
init_bounded_number a1(0.0,1.0,2)
init_bounded_number a2(0.0,1.0,3)
```

## Carrying out the minimization in a number of phases

For linear models one can simply estimate all the model parameters simultaneously. For nonlinear models often this simple approach does not work very well. It may be necessary to keep some of the parameters fixed during the initial part of the minimization process and carry out the minimization over a subset of the parameters. The other parameters are included into the minimization process in a number of phases until all of the parameters have been included. AD Model Builder provides support for this multi-phase approach. In the declaration of any initial parameter the last number, if present, determines the phase of the minimization during which this parameter is included (becomes active). If no number is present the initial parameter becomes active in phase 1. In this case `a0` has no phase number and so becomes active in phase 1. `a1` becomes active in phase 2, and `a2` becomes active in phase 3. In this example phase 3 is the last phase of the optimization.

It is often convenient to modify aspects of the code depending on which phase of the minimization procedure is the current phase or on whether a particular initial parameter is active. The function

```
current_phase()
```

returns an integer (object of type `int`) which is the value of the current phase. The function

```
last_phase()
```

returns the value “true” ( $\neq 0$ ) if the current phase is the last phase and false ( $= 0$ ) otherwise. If `xxx` is the name of any initial parameter the function

```
active(xxx)
```

returns the value “true” if `xxx` is active during the current phase and false otherwise.

After the minimization of the objective function has been completed AD Model Builder calculates the estimated covariance matrix for the initial parameters as well as any other desired parameters which have been declared to be of `sd_report` type. Often these additional parameters may involve considerable additional computational overhead. If the values of these parameters are not used in calculations proper, it is possible to only calculate them during the standard deviations report phase.

```
sd_phase()
```

The `sd_phase` function returns the value “true” if we are in the standard deviations report phase and “false” otherwise. It can be used in a conditional statement to determine whether to perform calculations associated with some `sd_report` object. When estimating

the parameters of a model by a multi-phase minimization procedure the default behavior of AD Model Builder is to carry out the default number of function evaluations until convergence is achieved in each stage. If we are only interested in the parameter estimates obtained after the last stage of the minimization it is often not necessary to carry out the full minimization in each stage. Sometimes considerable time can be saved by relaxing the convergence criterion in the initial stages of the optimization. The `RUNTIME_SECTION` allows the user to modify the default behavior of the function minimizer during the phases of the estimation process.

```
RUNTIME_SECTION
convergence_criteria .1, .1, .001
maximum_function_evaluations 20, 20, 1000
```

The `convergence_criteria` affects the criterion used by the function minimizer to decide when the optimization process has occurred. The function minimizer compares the maximum value of the vector of derivatives of the objective function with respect to the independent variables to the numbers after the `convergence_criteria` keyword. The first number is used in the first phase of the optimization, the second number in the second phase and so on. If there are more phases to the optimization than there are numbers the last number is used for the rest of the phases of the optimization. The numbers must be separated by commas. The spaces are optional. The `maximum_function_evaluations` keyword controls the maximum number of evaluations of the objective function which will be performed by the function minimizer in each stage of the minimization procedure.

## Natural resource management – the Schaeffer-Pella-Tomlinson Model

It is typical of many models in natural resource management that the model tends to be rather unstable numerically and in addition some of the model parameters are often poorly determined. Notwithstanding these difficulties it is often necessary to make decisions about resource management based on the analysis provided by these models. The example provides a good opportunity for presenting some more advanced features of AD Model Builder which are designed to overcome these difficulties.

The Schaeffer – Pella-Tomlinson model is employed in fisheries management. The model assumes that the total biomass of an exploited fish stock satisfies an ordinary differential equation of the form

$$\frac{dB}{dt} = rB \left( 1 - \left( \frac{B}{k} \right)^{m-1} \right) - FB \quad \text{where } m > 1 \quad (1.6)$$

(Hilborn and Walters page 303) where  $B$  is the biomass,  $F$  is the instantaneous fishing mortality rate,  $r$  is a parameter often referred to as the intrinsic rate of increase,  $k$  is the unfished equilibrium stock size,

$$C = FB \quad (1.7)$$

is the catch rate, and  $m$  is a parameter which determines where the maximum productivity of the stock occurs. If the value of  $m$  is fixed at 2 the model is referred to as the Schaeffer model. The explicit form of the difference equation corresponding to this differential equation is

$$B_{t+\delta} = B_t + rB_t\delta - rB_t\left(\frac{B_t}{k}\right)^{m-1}\delta - F_tB_t\delta \quad (1.8)$$

To get a semi-implicit form of this difference equation which has better numerical stability than the explicit version we replace some of the terms  $B_t$  on the right hand side of 1.8 by  $B_{t+\delta}$  to get

$$B_{t+\delta} = B_t + rB_t\delta - rB_{t+\delta}\left(\frac{B_t}{k}\right)^{m-1}\delta - F_tB_{t+\delta}\delta \quad (1.9)$$

and solve for  $B_{t+\delta}$  to give

$$B_{t+\delta} = \frac{B_t(1+r\delta)}{1+(r(B_t/k)^{m-1}+F_t)\delta} \quad (1.10)$$

The catch  $C_{t+\delta}$  over the period  $(t, t+\delta)$  is given by

$$C_{t+\delta} = F_tB_{t+\delta}\delta \quad (1.11)$$

## Bayesian considerations in the Pella–Tomlinson model

The parameter  $k$  is referred to as the carrying capacity or the unfished equilibrium biomass level because it is the value that the biomass of the population will eventually assume if there is no fishing. For a given value of  $k$  the parameter  $m$  determines the level of maximum productivity, that is the level of biomass  $B_{\text{MAX}}$  for which the removals from fishing can be the greatest.

$$B_{\text{MAX}} = \frac{k}{\sqrt[m-1]{m}}$$

For  $m = 2$  maximum productivity is obtained by that level of fishing pressure which reduces the stock to 50% of the carrying capacity. For the data available in many real fisheries problems the parameter  $m$  is very poorly determined. It is common practice therefore to simply assume that  $m = 2$ . Similarly, it is commonly assumed that the carrying capacity  $k$  does not change over time even though changes such as habitat degradation may well lead to changes in  $k$ .

We want to construct a statistical model where the carrying capacity can be varying slowly over time if there appears to be any information in the fisheries data supporting this hypothesis. What is meant by slowly? The answer to this question will depend on the

particular situation. For our purposes slowly means slowly enough so that the model has some chance of supplying a useful analysis of the situation at hand. We refer to this as the assumption of manageability. The point is that since we are going to use this model anyway to try and manage a resource we may as well assume that the model's assumptions are satisfied at least well enough so that we have some hope of success. This may seem extremely arbitrary, and it is. However it is not as arbitrary as assuming that the carrying capacity is constant.

We assume that  $k_{i+1} = k_i \exp(\kappa_i)$  where the  $\kappa_i$  are independent normally distributed random variables with mean 0. and that  $\log(m - 1)$  is normally distributed with mean 0. The parameters  $\log(k)$  are assumed to have the structure of a random walk which is the simplest type of time series. This Bayesian approach is a very simple method for including time series structure into the parameters of a nonlinear model.

We don't know the true catches  $C_i$  in each year. What we have are estimates  $C_i^{obs}$  of the catch. We assume that the quantities  $\log(C_i^{obs}/C_i)$  are normally distributed with mean 0.

Finally we must deal with the fishing mortality  $F$ . Estimates of  $F$  are not obtained directly. Instead what is observed is an index of fishing mortality, in this case fishing effort. We assume that for each year we have an estimate  $E_i$  of fishing effort and that the fishing mortality rate  $F_i$  in year  $i$  satisfies the relationship  $F_i = qE_i \exp(\eta_i)$  where  $q$  is a parameter referred to as the catchability and the  $\eta_i$  are normally distributed random variables with mean 0.

We assume that the variance of the  $\eta_i$  is 10 times the variance in the observed catch errors and that the variance of the  $\kappa_i$  is 0.1 times the variance in the observed catch errors. We assume that the variance in  $\log(m - 1)$  is 0.25. Then given the data, the Bayesian posterior distribution for the model parameters is proportional to

$$-(3n-1)/2 \log\left(\sum_{i=1}^n (\log(C_i^{obs}) - \log(C_i))^2 + .1 \sum_{i=1}^n \eta_i^2 + 10 \sum_{i=2}^n \kappa_i^2\right) - 2. \log(m-1)^2 \quad (1.12)$$

The number of initial parameters in the model (that is the number of independent variables in the function to be minimized) is  $2n + 4$ . For the halibut data there are 56 years of data which gives 116 parameters. As estimates of the model parameters we use the mode of the posterior distribution which can be found by minimizing -1 times expression (0.8). The covariance matrix of the model parameters are estimated by computing the inverse of the hessian of expression (0.8) at the minimum. The template for the model follows. To improve the readability the entire template has been included. The various sections are discussed below.

```
DATA_SECTION
  init_int nobs;
  init_matrix data(1,nobs,1,3)
  vector obs_catch(1,nobs);
  vector cpue(1,nobs);
  vector effort(1,nobs);
  number avg_effort
```

```

INITIALIZATION_SECTION
  m 2.
  beta 1.
  r 1.
PARAMETER_SECTION
  init_bounded_number q(0.,1.)
  init_bounded_number beta(0.,5.)
  init_bounded_number r(0.,5,2)
  init_number log_binit(2)
  init_bounded_dev_vector effort_devs(1,nobs,-5.,5.,3)
  init_bounded_number m(1,10.,4)
  init_bounded_vector k_devs(2,nobs,-5.,5.,4)
  number binit
  vector pred_catch(1,nobs)
  vector biomass(1,nobs)
  vector f(1,nobs)
  vector k(1,nobs)
  vector k_trend(1,nobs)
  sdreport_number k_1
  sdreport_number k_last
  sdreport_number k_change
  sdreport_number k_ratio
  sdreport_number B_projected
  number tmp_mort;
  number bio_tmp;
  number c_tmp;
  objective_function_value ff;
PRELIMINARY_CALCS_SECTION
  // get the data out of the data matrix into
  obs_catch=column(data,2);
  cpue=column(data,3);
  // divide the catch by the cpue to get the effort
  effort=elem_div(obs_catch,cpue);
  // normalize the effort and save the average
  double avg_effort=mean(effort);
  effort/=avg_effort;
  cout << " beta" << beta << endl;
PROCEDURE_SECTION
  // calculate the fishing mortality
  calculate_fishing_mortality();
  // calculate the biomass and predicted catch
  calculate_biomass_and_predicted_catch();
  // calculate the objective function
  calculate_the_objective_function();

FUNCTION calculate_fishing_mortality
  // calculate the fishing mortality
  f=q*effort;
  if (active(effort_devs)) f=elem_prod(f,exp(effort_devs));

FUNCTION calculate_biomass_and_predicted_catch
  // calculate the biomass and predicted catch
  if (!active(log_binit))
  {
    log_binit=log(obs_catch(1)/(q*effort(1)));
  }
  binit=exp(log_binit);
  biomass[1]=binit;

```



```

if (active(k_devs))
{
  k(1)=binit/beta;
  for (int i=2;i<=nobs;i++)
  {
    k(i)=k(i-1)*exp(k_devs(i));
  }
}
else
{
  // set the whole vector equal to the constant k value
  k=binit/beta;
}
// only calculate these for the standard deviation report
if (sd_phase)
{
  k_1=k(1);
  k_last=k(nobs);
  k_ratio=k(nobs)/k(1);
  k_change=k(nobs)-k(1);
}
// two time steps per year desired
int nsteps=2;
double delta=1./nsteps;
// Integrate the logistic dynamics over n time steps per year
for (int i=1; i<=nobs; i++)
{
  bio_tmp=1.e-20+biomass[i];
  c_tmp=0.;
  for (int j=1; j<=nsteps; j++)
  {
    //This is the new biomass after time step delta
    bio_tmp=bio_tmp*(1.+r*delta)/
      (1.+ (r*pow(bio_tmp/k(i),m-1.))+f(i))*delta );
    // This is the catch over time step delta
    c_tmp+=f(i)*delta*bio_tmp;
  }
  pred_catch[i]=c_tmp;          // This is the catch for this year
  if (i<nobs)
  {
    biomass[i+1]=bio_tmp;// This is the biomass at the begining of the next
  }
  // year
  else
  {
    B_projected=bio_tmp; // get the projected biomass for std dev report
  }
}
}

FUNCTION calculate_the_objective_function
if (!active(effort_devs))
{
  ff=nobs/2.*log(norm2(log(obs_catch)-log(1.e-10+pred_catch)));
}
else if(!active(k_devs))
{
  ff= .5*(size_count(obs_catch)+size_count(effort_devs))*
    log(norm2(log(obs_catch)-log(1.e-10+pred_catch))
    +0.1*norm2(effort_devs));
}

```

```

}
else
{
  ff= .5*( size_count(obs_catch)+size_count(effort_devs)
    +size_count(k_devs) )*
    log(norm2(log(obs_catch)-log(pred_catch))
    + 0.1*norm2(effort_devs)+10.*norm2(k_devs));
}
// Bayesian contribution for Pella Tomlinson m
ff+=2.*square(log(m-1.));
if (current_phase()<3)
{
  ff+=1000.*square(log(mean(f)/.4));
}

```

The data are contained in three columns, with the catch and catch per unit effort data contained in the second and third columns. The matrix `data` is defined in order to read the data. The second and third columns of `data` which we are interested in will then be put into the vectors `obs_catch` and `cpue`. (Later we get the fishing effort by dividing the `obs_catch` by the `cpue`.)

```

DATA_SECTION
  init_int nobs
  init_matrix data(1,nobs,1,3)
  vector obs_catch(1,nobs)
  vector cpue(1,nobs)
  vector effort(1,nobs)
  number avg_effort

```

The `INITIALIZATION_SECTION` is used to define default values for some model parameters if the standard default provided by AD Model Builder is not acceptable. If the model finds the parameter file (whose default name is `admodel.par`) it will read in the initial values for the parameters from there. Otherwise the default values will be used unless the parameters appear in the `INITIALIZATION_SECTION` in which case those values will be used.

```

INITIALIZATION_SECTION
  m 2.
  beta 1.
  r 1.

```

The `PARAMETER_SECTION` for this model introduces several new features of AD Model Builder. The statement `init_bounded_number r(0.,5.,2)` declares an initial parameter whose value will be constrained to lie between 0.0 and 5.0. It is often necessary to put bounds on the initial parameters in nonlinear models to get stable model performance. This is accomplished in AD Model Builder simply by declaring the initial parameter to be bounded and providing the desired bounds. The default initial value for a bounded object is the average of the lower and upper bounds.

The third number 2 in the declaration determines that this initial parameter will not be made active until the second phase of the minimization. This introduces the concept of phases in the minimization process.

As soon as nonlinear statistical models become a bit complicated one often finds that simply attempting to estimate all the parameters simultaneously does not work very well. In short “you can’t get there from here”. A better strategy is to keep some of the parameters fixed and to first minimize the function with respect to the other parameters. More parameters are added in a stepwise relaxation process. In AD Model Builder each step of this relaxation process is termed a phase. The parameter `r` is not allowed to vary until the second phase. Initial parameters which are allowed to vary will be termed active. In the first phase the active parameters are `beta` and `q`. The default phase for an initial parameter is phase 1 if no phase number is included in its declaration. The phase number for an initial parameter is the last number in the declaration for that parameter. The general order for the arguments in the definition of any initial parameter is the size data for a vector or matrix object if needed, the bounds for a bounded object if needed, followed by the phase number if desired.

It is often a difficult problem to decide what the order of relaxation for the initial parameters should be. This must sometimes be done by trial and error. However AD Model Builder makes the process a lot simpler. One only needs to change the phase numbers of the initial parameters in the `PARAMETER_SECTION` and recompile the program.

Often in statistical modeling it is useful to regard a vector of quantities  $x_i$  as consisting of an overall mean,  $\mu$ , and a set of deviations from that mean,  $\delta_i$ , so that

$$x_i = \mu + \delta_i \quad \text{where} \quad \sum_i \delta_i = 0$$

AD Model Builder provides support for this modeling construction with the `init_bounded_dev_vector` declaration. The components of an object created by this declaration will automatically sum to 0 without any user intervention. The line

```
init_bounded_dev_vector effort_devs(1,nobs,-5.,5.,3)
```

declares `effort_devs` to be this kind of object. The bounds `-5.,5.` control the range of the deviations. Putting reasonable bounds on such deviations often improves the stability of the estimation procedure.

AD Model Builder has `sdreport_number`, `sdreport_vector`, and `sdreport_matrix` declarations in the `PARAMETER_SECTION`. These objects behave the same as `number`, `vector`, and `matrix` objects with the additional property that they are included in the report of the estimated standard deviations and correlation matrix.

For example merely by including the statement `sdreport_number B_projected` one can obtain the estimated standard deviation of the biomass projection for the next year. (Of course you must also set `B_projected` equal to the projected biomass. This is done in the `PROCEDURE_SECTION`.)

```
PARAMETER_SECTION
  init_bounded_number q(0.,1.)
  init_bounded_number beta(0.,5.)
```

```

init_bounded_number r(0.,5,2)
init_number log_binit(2)
init_bounded_dev_vector effort_devs(1,nobs,-5.,5.,3)
init_bounded_number m(1,10.,4)
init_bounded_vector k_devs(2,nobs,-5.,5.,4)
number binit
vector pred_catch(1,nobs)
vector biomass(1,nobs)
vector f(1,nobs)
vector k(1,nobs)
vector k_trend(1,nobs)
sdreport_number k_1
sdreport_number k_last
sdreport_number k_change
sdreport_number k_ratio
sdreport_number B_projected
number tmp_mort;
number bio_tmp;
number c_tmp;
objective_function_value ff;

```

The PRELIMINARY\_CALCS\_SECTION carries out a few simple operations on the data. The model expects to have catch and effort data, but the input file contained catch and cpue (catch/effort) data. We divide the catch data by the cpue data to get the effort data. The AUTODIF operation `elem_div` which performs element-wise divisions of vector objects is used. As usual the same thing could have been accomplished by employing a loop and writing element-wise code. The effort data are then normalized, that is, they are divided by their average so that their average becomes 1. This is done so that we have a good idea what the catchability parameter  $q$  should be to give reasonable values for the fishing mortality rate (since  $F = qE$ ).

Notice that the PRELIMINARY\_CALCS\_SECTION section is C++ code so that statements must be ended with a `;`. `extract` a column from a matrix

```

PRELIMINARY_CALCS_SECTION
// get the data out of the data matrix into
obs_catch=column(data,2);
cpue=column(data,3);
// divide the catch by the cpue to get the effort
effort=elem_div(obs_catch,cpue);
// normalize the effort and save the average
double avg_effort=mean(effort);
effort/=avg_effort;

```

The PROCEDURE\_SECTION contains several new AD Model Builder features. Some have to do with the notion of carrying out the minimization in a number of steps or phases. The line

```

if (active(effort_devs)) f=elem_prod(f,exp(effort_devs));

```

introduces the `active` function. This function can be used on any initial parameter and will return a value “true” if that parameter is active in the current phase. The idea here is that if the initial parameters `effort_devs` are not active then since their value is 0 carrying

out the calculations will have no effect and we can save time by avoiding the calculations. The `active` function is also used in the statement

```
if (!active(log_binit))
{
  log_binit=log(obs_catch(1)/(q*effort(1)));
}
```

The idea is that if the `log_binit` initial parameter (this is the logarithm of the biomass at the beginning of the first year) is not active then we set it equal to the value which produces the observed catch (using the relationship  $C = qEB$  so that  $B = C/(qE)$ ). The `active` function is also used in the calculations of the objective function so that unnecessary calculations are avoided.

The following code helps to deal with convergence problems in this type of nonlinear model. The problem is that the starting parameter values are often so bad that the optimization procedure will try to make the population very large and the exploitation rate very small because this is the best local solution near the starting parameter values. To circumvent this problem we include a penalty function to keep the average value of the fishing mortality rate `f` close to 0.2 during the first two phases of the minimization. In the final phase the size of the penalty term is reduced to a very small value. The function `current_phase()` returns the value of the current phase of the minimization.

```
if (current_phase()<3)
{
  ff+=1000.*square(log(mean(f)/.4));
}
```

## Using FUNCTIONS to improve code organization

Subroutines or functions are used to improve the organization of the code. The code for the main part of the `PROCEDURE_SECTION` which invokes the `FUNCTIONS` should be placed at the top of the `PROCEDURE_SECTION`.

```
PROCEDURE_SECTION
// calculate the fishing mortality
calculate_fishing_mortality();
// calculate the biomass and predicted catch
calculate_biomass_and_predicted_catch();
// calculate the objective function
calculate_the_objective_function();
```

There are three user-defined functions called at the beginning of the `PROCEDURE_SECTION`. The code to define the `FUNCTIONS` comes next. To define a function whose name is `name` the template directive `FUNCTION name` is used. Notice that no parentheses `()` are used in the definition of the function, but to call the function the statement takes the form `name()`;

## A fisheries catch-at-age model

This section describes a simple catch-at age model. The data input to this model include estimates of the numbers at age caught by the fishery each year and estimates the fishing effort each year. This example introduces AD Model Builder's ability to automatically calculate profile likelihoods for carrying out Bayesian inference. To cause the profile likelihood calculations to be carried out use the `-lprof` command line argument.

Let  $i$  index fishing years  $1 \leq i \leq n$  and  $j$  index age classes with  $1 \leq j \leq r$ . The instantaneous fishing mortality rate is assumed to have the form  $F_{ij} = qE_i s_j \exp(\delta_i)$  where  $q$  is called the catchability,  $E_i$  is the observed fishing effort,  $s_j$  is an age-dependent effect termed the selectivity, and the  $\delta_i$  are deviations from the expected relationship between the observed fishing effort and the resulting fishing mortality. The  $\delta_i$  are assumed to be normally distributed with mean 0. The instantaneous natural mortality rate  $M$  is assumed to be independent of year and age class. It is not estimated in this version of the model. The instantaneous total mortality rate is given by  $Z_{ij} = F_{ij} + M$ . The survival rate is given by  $S_{ij} = \exp(-Z_{ij})$ . The number of age class  $j$  fish in the population in year  $i$  is denoted by  $N_{ij}$ . The relationship  $N_{i+1,j+1} = N_{ij} S_{ij}$  is assumed to hold. Note that using this relationship if one knows  $S_{ij}$  then all the  $N_{ij}$  can be calculated from knowledge of the initial population in year 1,  $N_{11}, N_{12}, \dots, N_{1r}$  and knowledge of the recruitment in each year  $N_{21}, N_{31}, \dots, N_{n1}$ .

The purpose of the model is to estimate quantities of interest to managers such as the population size and exploitation rates and to make projections about the population. In particular we can get an estimate of the numbers of fish in the population in year  $n + 1$  for age classes 2 or greater from the relationship  $N_{n+1,j+1} = N_{nj} S_{nj}$ . If we have estimates  $m_j$  for the mean weight at age  $j$ , then the projected biomass level  $B_{n+1}$  of age class 2+ fish for year  $n + 1$  can be computed from the relationship  $B_{n+1} = \sum_{j=2}^r m_j N_{n+1,j}$ .

Besides getting a point estimate for quantities of interest like  $B_{n+1}$  we also want to get an idea of how well determined the estimate is. AD Model Builder has completely automated the process of deriving good confidence limits for these parameters in a Bayesian context. One simply needs to declare the parameter to be of type `likeprof_number`. The results are given in the section on Bayesian inference.

The code for the catch-at-age model is:

```
DATA_SECTION
// the number of years of data
init_int nyrs
// the number of age classes in the population
init_int nages
// the catch-at-age data
init_matrix obs_catch_at_age(1,nyrs,1,nages)
//estimates of fishing effort
init_vector effort(1,nyrs)
// natural mortality rate
init_number M
// need to have relative weight at age to calculate biomass of 2+
vector relwt(2,nages)
```

```

INITIALIZATION_SECTION
  log_q -1
  log_P 5
PARAMETER_SECTION
  init_number log_q(1) // log of the catchability
  init_number log_P(1) // overall population scaling parameter
  init_bounded_dev_vector log_sel_coff(1,nages-1,-15.,15.,2)
  init_bounded_dev_vector log_relpop(1,nyrs+nages-1,-15.,15.,2)
  init_bounded_dev_vector effort_devs(1,nyrs,-5.,5.,3)
  vector log_sel(1,nages)
  vector log_initpop(1,nyrs+nages-1);
  matrix F(1,nyrs,1,nages) // the instantaneous fishing mortality
  matrix Z(1,nyrs,1,nages) // the instantaneous total mortality
  matrix S(1,nyrs,1,nages) // the survival rate
  matrix N(1,nyrs,1,nages) // the predicted numbers at age
  matrix C(1,nyrs,1,nages) // the predicted catch at age
  objective_function_value f
  sdreport_number avg_F
  sdreport_vector predicted_N(2,nages)
  sdreport_vector ratio_N(2,nages)
  likeprof_number pred_B
PRELIMINARY_CALC_SECTION
  // this is just to invent some relative average
  // weight numbers
  relwt.fill_seqadd(1.,1.);
  relwt=pow(relwt,.5);
  relwt/=max(relwt);
PROCEDURE_SECTION
  // example of using FUNCTION to structure the procedure section
  get_mortality_and_survival_rates();

  get_numbers_at_age();

  get_catch_at_age();

  evaluate_the_objective_function();

FUNCTION get_mortality_and_survival_rates
  // calculate the selectivity from the sel_coffs
  for (int j=1;j<nages;j++)
  {
    log_sel(j)=log_sel_coff(j);
  }
  // the selectivity is the same for the last two age classes
  log_sel(nages)=log_sel_coff(nages-1);

  // This is the same as F(i,j)=exp(log_q)*effort(i)*exp(log_sel(j));
  F=outer_prod(mfexp(log_q)*effort,mfexp(log_sel));
  if (active(effort_devs))
  {
    for (int i=1;i<=nyrs;i++)
    {
      F(i)=F(i)*exp(effort_devs(i));
    }
  }
  // get the total mortality
  Z=F+M;
  // get the survival rate

```

```

S=mfexp(-1.0*Z);

FUNCTION get_numbers_at_age
  log_initpop=log_relpop+log_P;
  for (int i=1;i<=nyrs;i++)
  {
    N(i,1)=mfexp(log_initpop(i));
  }
  for (int j=2;j<=nages;j++)
  {
    N(1,j)=mfexp(log_initpop(nyrs+j-1));
  }
  for (i=1;i<nyrs;i++)
  {
    for (j=1;j<nages;j++)
    {
      N(i+1,j+1)=N(i,j)*S(i,j);
    }
  }
  // calculated predicted numbers at age for next year
  for (j=1;j<nages;j++)
  {
    predicted_N(j+1)=N(nyrs,j)*S(nyrs,j);
    ratio_N(j+1)=predicted_N(j+1)/N(1,j+1);
  }
  // calculate predicted biomass for profile
  // likelihood report
  pred_B=predicted_N *relwt;

FUNCTION get_catch_at_age
  C=elem_prod(elem_div(F,Z),elem_prod(1.-S,N));

FUNCTION evaluate_the_objective_function
  // penalty functions to "regularize" the solution
  f+=.01*norm2(log_relpop);
  avg_F=sum(F)/double(size_count(F));
  if (last_phase())
  {
    // a very small penalty on the average fishing mortality
    f+= .001*square(log(avg_F/.2));
  }
  else
  {
    // use a large penalty during the initial phases to keep the
    // fishing mortality high
    f+= 1000.*square(log(avg_F/.2));
  }
  // errors in variables type objective function with errors in
  // the catch at age and errors in the effort fishing mortality
  // relationship
  if (active(effort_devs)
  {
    // only include the effort_devs in the objective function if
    // they are active parameters
    f+=0.5*double(size_count(C)+size_count(effort_devs))
      * log( sum(elem_div(square(C-obs_catch_at_age),.01+C))
      + 0.1*norm2(effort_devs));
  }

```



```

else
{
// objective function without the effort_devs
f+=0.5*double(size_count(C))
  * log( sum(elem_div(square(C-obs_catch_at_age),.01+C)));
}
REPORT_SECTION
report << "Estimated numbers of fish " << endl;
report << N << endl;
report << "Estimated numbers in catch " << endl;
report << C << endl;
report << "Observed numbers in catch " << endl;
report << obs_catch_at_age << endl;
report << "Estimated fishing mortality " << endl;
report << F << endl;

```

This model employs several instances of the `init_bounded_dev_vector` type. This type consists of a vector of numbers which sum to 0, that is they are deviations from a common mean, and are bounded. For example the quantities `log_relpop` are used to parameterize the logarithm of the variations in year class strength of the fish population. Putting bounds on the magnitude of the deviations helps to improve the stability of the model. The bounds are from -15.0 to 15.0 which gives the estimates of relative year class strength a dynamic range of  $\exp(30.0)$ .

The `FUNCTION` keyword has been employed a number of times in the `PARAMETER_SECTION` to help structure the code. A function is defined simply by using the `FUNCTION` keyword followed by the name of the function.

```
FUNCTION get_mortality_and_survival_rates
```

Don't include the parentheses or semicolon here. To use the function simply write its name in the procedure section.

```
get_mortality_and_survival_rates();
```

You must include the parentheses and the semicolon here.

The `REPORT_SECTION` shows how to generate a report for an AD Model Builder program. The default report generating machinery utilizes the C++ stream formalism. You don't need to know much about streams to make a report, but a few comments are in order. The stream formalism associates stream object with a file. In this case the stream object associated with the AD Model Builder report file is `report`. To write an object `xxx` into the report file you insert the line

```
report << xxx;
```

into the `REPORT_SECTION`. If you want to skip to a new line after writing the object you can include the stream manipulator `endl` as in

```
report << "Estimated numbers of fish " << endl;
```

Notice that the stream operations know about common C objects such as strings, so that it is a simple matter to put comments or labels into the report file.

## Bayesian inference and the profile likelihood

AD Model Builder enables one to quickly build models with large numbers of parameters – this is especially useful for employing Bayesian analysis. Traditionally however it has been difficult to interpret the results of analysis using such models. In a Bayesian context the results are represented by the posterior probability distribution for the model parameters. To get exact results from the posterior distribution it is necessary to evaluate integrals over large dimensional spaces and this can be computationally intractable. AD Model Builder provides an approximations to these integrals in the form of the profile likelihood. The profile likelihood can be used to estimates for extreme values (such as estimating a value  $\beta$  so that for a parameter  $b$  the probability that  $b < \beta \approx 0.10$  or the probability that  $b > \beta \approx 0.10$ ) for any model parameter. To use this facility simply declare the parameter of interest to be of type `likeprof_number` in the `PARAMETER_SECTION` and assign the correct value to the parameter in the `PROCEDURE_SECTION`.

The code for the catch at age model estimates the profile likelihood for the projected biomass of age class 2+ fish. (Age class 2+ has been used to avoid the extra problem of dealing with the uncertainty of the recruitment of age class 1 fish). As a typical application of the method, the user of the model can estimate the probability that the biomass of fish for next year will be larger or smaller than a certain value. Estimates like these are obviously of great interest to managers of natural resources.

The profile likelihood report for a variable is in a file with the same name as the variable (truncated to eight letters, if necessary, with the suffix `.PLT` appended). For this example the report is in the file `PRED_B.PLT`. Part of the file is shown here.

```
pred_B:
Profile likelihood
-1411.23 1.1604e-09
-1250.5 1.71005e-09
-1154.06 2.22411e-09
..... // skip some here
.....
278.258 2.79633e-05
324.632 5.28205e-05
388.923 6.89413e-05
453.214 8.84641e-05
517.505 0.0001116
581.796 0.000138412
.....
.....
1289 0.000482459
1353.29 0.000494449
1417.58 0.000503261
1481.87 0.000508715
1546.16 0.0005107
1610.45 0.000509175
1674.74 0.000504171
1739.03 0.000490788
1803.32 0.000476089
1867.61 0.000460214
```

```

1931.91 0.000443313
1996.2 0.000425539
2060.49 0.000407049
2124.78 0.000388
2189.07 0.00036855
.....
.....
4503.55 2.27712e-05
4599.98 2.00312e-05
4760.71 1.48842e-05
4921.44 1.07058e-05
5082.16 7.45383e-06
.....
.....
6528.71 6.82689e-07
6689.44 6.91085e-07
6850.17 7.3193e-07
Minimum width confidence limits:
      significance level  lower bound  upper bound
              0.90          572.537    3153.43
              0.95          453.214    3467.07
              0.975          347.024    3667.76

One sided confidence limits for the profile likelihood:

The probability is      0.9 that pred_B is greater than 943.214
The probability is      0.95 that pred_B is greater than 750.503
The probability is      0.975 that pred_B is greater than 602.507

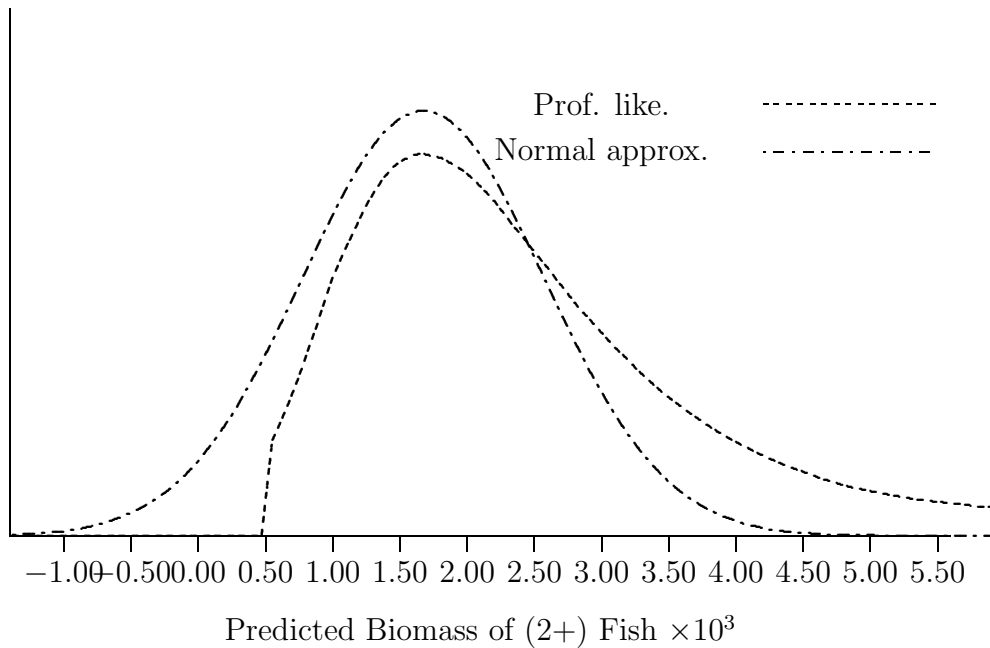
The probability is      0.9 that pred_B is less than 3173.97
The probability is      0.95 that pred_B is less than 3682.75
The probability is      0.975 that pred_B is less than 4199.03

```

The file contains the probability density function and the approximate confidence limits for the the profile likelihood and the normal approximation. Since the format is the same for both, we only discuss the profile likelihood here. The first part of the report contains pairs of numbers  $(x_i, y_i)$  which consist of values of the parameter in the report (in this case PRED\_B and the estimated value for the probability density associated with that parameter at the point. The probability that the parameter lies in the interval  $x_r \leq x \leq x_s$ ) where  $x_r < x_s$  can be estimated from the sum

$$\sum_{i=r}^s (x_{i+1} - x_i) y_i.$$

The reports of the one and two sided confidence limits for the parameter were produced this way. Also a plot of  $y_i$  verses  $x_i$  gives the user an indication of what the probability distribution of the parameter looks like.



The the profile likelihood indicates the fact that the biomass can not be less than zero. The normal approximation is not very useful for calculating the probability that the biomass is very low – a question of great interest to managers who are probably not going to be impressed by the knowledge that there is an estimated probability of 0.975 that the biomass is greater than -52.660.

One sided confidence limits for the normal approximation

The probability is 0.9 that pred\_B is greater than 551.235  
 The probability is 0.95 that pred\_B is greater than 202.374  
 The probability is 0.975 that pred\_B is greater than -52.660

## Saving the output from profile likelihood to use as starting values for MCMC analysis

If the profile likelihood calculations are carried out with the `-prsave` option the values of the independent variables for each point on the profile are saved in a file named `xxx.pv1` where `xxx` is the name of the variable being profiled.

```
#Step -8
#num sigmas -27
-2.96325 6.98069 -2.96893 -1.15811 0.417864 1.5352 1.50556
0.668417 1.29106 2.04238 1.85167 1.02342 1.03264 1.35247
1.5832 1.87033 1.67212 0.984254 -0.58013 -8.10159 0.757686
0.958038 0.414446 -1.48443 -2.57572 -4.09184 -0.869426 -0.545055
-0.333125 -0.350978 -0.487261 -0.123192 -0.158569 -0.434328
-0.609651 -0.684244 -0.405214 5.00104
#Step -7
```

```

#num sigmas -22
// .....
#Step 7
#num sigmas 22
-5.94034 9.29211 -2.6122 0.0773101 1.54853 1.91895 0.578923
-1.51152 0.0124827 0.712157 0.520084 -0.202059 -0.0505122
0.284112 0.469956 0.731273 0.664325 0.642344 0.691073
-1.10233 -0.362781 0.034522 0.0127999 -0.538117 -0.575466
-1.94386 -0.544077 -0.0349702 0.349352 0.355073 0.237236
0.335559 0.177427 -0.0507647 -0.167382 -0.303103 -0.249956 -0.104393
#Step 8
#num sigmas 27
-6.09524 9.43103 -2.59874 0.0930842 1.55938
1.91285 0.561478 -1.52804 -0.0139936 0.687758 0.502089
-0.212203 -0.0519722 0.287149 0.474422 0.739316 0.678415
0.663857 0.71933 -1.07637 -0.387684 0.0146463 0.00647923
-0.530625 -0.566471 -1.93414 -0.521944 -0.0111346 0.372352
0.372706 0.247599 0.333505 0.171122 -0.0585298 -0.177735
-0.319115 -0.273111 -0.135715

```

To use the values as a starting point for the MCMC analysis use a text editor to put the desired starting values in a file by themselves. Suppose that the file name is `mcmc.dat`. Run the MCMC analysis with the option `-mcpin mcmc.dat` and it will begin the MCMC analysis from that file.

## The profile likelihood Calculations

We have been told that the profile likelihood as calculated in AD Model Builder for dependent variables may differ from that calculated by other authors. This section will clarify what we mean by the term and motivate our calculation.

Let  $(x_1, \dots, x_n)$  be  $n$  independent variables,  $f(x_1, \dots, x_n)$  be a probability density function and  $g$  denote a dependent variable, that is, a real valued function of  $(x_1, \dots, x_n)$ . The profile likelihood calculation for  $g$  is intended to produce an approximation to the probability density function for  $g$ .

Consider first the case where  $g$  is equal to one of the independent variables, say  $g = x_1$ . In this simple case the marginal distribution of  $x_1$  is give by the integral

$$\int f(x_1, \dots, x_n) dx_2 dx_3 \dots dx_n \tag{1.13}$$

The use of the profile likelihood in this case is based on the assumption (or hope) that there exists a constant  $\lambda$  independent of  $x_1$  such that  $\lambda \max_{x_2, \dots, x_n} \{f(x_1, \dots, x_n)\}$  is a good approximation to this integral.

This approach should be useful for a lot of applications based on the fact that the central limit theorem implies that for a lot of observations the posterior proability distribution is more or less well approximated by a multivariate normal distribution and for such distributions the assumptions holds exactly. So the profile likelihood is calculated by calculating the

conditional maximum of the likelihood function and then normalizing it so that it integrates to 1.

For an arbitrary dependent variable the situation is a bit more complicated. A good approximation to a probability distribution should have the property of parameter invariance, that is  $Pr\{a \leq x \leq b\} = Pr\{h(a) \leq h(x) \leq h(b)\}$  for any monotonically increasing function  $h$ . To achieve the property of parameter invariance we modify the definition of profile likelihood for dependent variables.

Fix a value  $g_0$  for  $g$  and consider the integral

$$\int_{\{x: g_0 - \epsilon/2 \leq g(x) \leq g_0 + \epsilon/2\}} f(x_1, \dots, x_n) dx_1 dx_2 \dots dx_n$$

which is the probability that  $g(x)$  has a value between  $g_0 - \epsilon/2$  and  $g_0 + \epsilon/2$ . This probability depends on two quantities, the value of  $f(x)$  and the thickness of the region being integrated over. We approximate  $f(x)$  by its maximum value  $\hat{f}(g) = \max_{\{x: g(x)=g_0\}} \{f(x)\}$ . For the thickness we have  $g(\hat{x} + h) \approx g(\hat{x}) + \langle \nabla g(\hat{x}), h \rangle = \epsilon/2$  where  $h$  is a vector perpendicular to the level set of  $g$  at  $\hat{x}$ . However  $\nabla g$  is also perpendicular to the level set so  $\langle \nabla g(\hat{x}), h \rangle = \|\nabla g(\hat{x})\| \|h\|$  so that  $\|h\| = \epsilon / (2\|\nabla g(\hat{x})\|)$ . Thus the integral is approximated by  $\epsilon \hat{f}(g) / \|\nabla g(\hat{x})\|$  and taking the derivative with respect to  $\epsilon$  yields  $\hat{f}(g) / \|\nabla g(\hat{x})\|$  which is the profile likelihood expression for a dependent variable. For an independent variable  $\|\nabla g(\hat{x})\| = 1$  so that our definition of the profile likelihood corresponds to the usual one in this case.

## Modifying the profile likelihood approximation procedure

The functions `set_stepnumber()` and `set_stepsize()` can be used to modify the number of points used to approximate the profile likelihood or to change the stepsize between the points. This can be carried out in the `PRELIMINARY_CALCS_SECTION`. If `u` has been declared to be of type `likeprof_number`

```
PRELIMINARY_CALCS_SECTION
  u.set_stepnumber(10); // default value is 8
  u.set_stepsize(0.2); // default value is 0.5
```

will set the number of steps equal to 21 (from -10 to 10) and will set the step size equal to 0.2 times the estimated standard deviation for the parameter `u`.

## Changing the default file names for data and parameter input

The following code fragment illustrates how the files used for input of the data and parameter values can be changed. This code has been taken from the example `catage.tpl` and modified. In the `DATA_SECTION`, the data are first read in from the file `catch.dat`. Then the effort data are read in from the file `effort.dat`. The remainder of the data are read in from the file `catch.dat`. It is necessary to save the current file position in an object of type `streampos`. This object is used to position the file properly. The escape sequence `!!` can be used to include one line of the users's code into the `DATA_SECTION` or `PARAMETER_SECTION`. It is more compact than the `LOCAL_CALCS` construction.

```
DATA_SECTION
// will read data from file catchdat.dat
!! ad_comm::change_datafile_name("catchdat.dat");
  init_int nyrs
  init_int nages
  init_matrix obs_catch_at_age(1,nyrs,1,nages)
// now read the effort data from the file effort.dat and save the current
// file position in catchdat.dat in the object tmp
!! streampos tmp = ad_comm::change_datafile_name("effort.dat");
  init_vector effort(1,nyrs)
// now read the rest of the data from the file catchdat.dat
// including the ioption argument tmp will reset the file to that position
!! ad_comm::change_datafile_name("catchdat.dat",tmp);
  init_number M

// ....

PARAMETER_SECTION
// will read parameters from file catch.par
!! ad_comm::change_parfile_name("catch.par");
```

## Using the subvector operation to avoid writing loops

If `v` is a vector object then for integers `l` and `u` the expression `v(l,u)` is a vector object of the same type with minimum valid index `l` and maximum valid index `u` (Of course `l` and `u` must be within the valid index range for `v` and `l` must be less than or equal to `u`). The subvector formed by this operation can be used on both sides of the equals sign in an arithmetic expression. The number of loops which must be written can be significantly reduced in this manner. We shall use the subvector operator to remove some of the loops in the catch-at-age model code.

```
// calculate the selectivity from the sel_coffs
for (int j=1;j<nages;j++)
{
  log_sel(j)=log_sel_coff(j);
}
// the selectivity is the same for the last two age classes
log_sel(nages)=log_sel_coff(nages-1);

// same code using the subvector operation
log_sel(1,nage-1)=log_sel_coff;
```

```
// the selectivity is the same for the last two age classes
log_sel(nages)=log_sel_coff(nages-1);
```

Notice that `log_sel(1,nage-1)` is not a distinct vector from `log_sel`. This means that an assignment to `log_sel(1,nage-1)` is an assignment to a part of `log_sel`. The next example is a bit more complicated. It involves taking a row of a matrix, to form a vector, forming a subvector, and changing the valid index range for the vector.

```
// loop form of the code
for (i=1;i<nyrs;i++)
{
  for (j=1;j<nages;j++)
  {
    N(i+1,j+1)=N(i,j)*S(i,j);
  }
}

// can only eliminate the inside loop
for (i=1;i<nyrs;i++)
{
  // ++ increments the index bounds by 1
  N(i+1)(2,nyrs)=++elem_prod(N(i)(1,nage-1),S(i)(1,nage-1));
}
```

Notice that `N(i+1)` is a vector object so that `N(i+1)(2,nyrs)` is a subvector of `N(i)`. Another point is that `elem_prod(N(i)(1,nage-1),S(i)(1,nage-1))` is a vector object with minimum valid index 1 and maximum valid index `nyrs-1`. The operator `++` applied to a subvector increments the valid index range by 1 so that it has the same range of valid index values as `N(i+1)(2,nyrs)`. The operator `--` would decrement the valid index range by 1.

## The use of higher dimensional arrays

The example contained in the file `FOURD.TPL` illustrates some aspects of the use of three and four dimensional arrays. There are now examples of the use of arrays up to dimension 7 in the documentation<sup>2</sup>.

```
DATA_SECTION
  init_4darray d4(1,2,1,2,1,3,1,3)
  init_3darray d3(1,2,1,3,1,3)
PARAMETER_SECTION
  init_matrix M(1,3,1,3)
  4darray p4(1,2,1,2,1,3,2,3)
  objective_function_value f
PRELIMINARY_CALCS_SECTION
  for (int i=1;i<=3;i++)
  {
    M(i,i)=1; // set M equal to the identity matrix to start
  }
PROCEDURE_SECTION
```

---

<sup>2</sup>See the chapter on regime switching models for an example of the use of higher dimensional arrays.



```

for (int i=1;i<=2;i++)
{
  for (int j=1;j<=2;j++)
  {
    // d4(i,j) is a 3x3 matrix -- d3(i) is a 3x3 matrix
    // d4(i,j)*M is matrix multiplication -- inv(M) is matrix inverse
    f+= norm2( d4(i,j)*M + d3(i)+ inv(M) );
  }
}
}
REPORT_SECTION
report << "Printout of a 4 dimensional array" << endl << endl;
report << d4 << endl << endl;
report << "Printout of a 3 dimensional array" << endl << endl;
report << d3 << endl << endl;

```

In the DATA\_SECTION you can use 3darrays, 4darrays, up to 7darrays and init\_3darrays, init\_4darrays up to init\_7darrays. In the PARAMETER\_SECTION you can use 3darrays, 4darrays, up to 7darrays and init\_3darrays, init\_4darrays up to init\_5darrays at the time of writing.

If d4 is a 4darray then d4(i) is a three dimensional array and d4(i,j) is a matrix object so that d4(i,j)\*M is matrix multiplication. Similarly if d3 is a 3darray then d3(i) is a matrix object so that d4(i,j)\*M + d3(i) +inv(M) combines matrix multiplication, matrix inversion, and matrix addition.

## The TOP\_OF\_MAIN section

The TOP\_OF\_MAIN section is intended to allow the programmer to insert any desired C++ code at the top of the main() function in the program. The code is copied literally from the template to the program. This section can be used to set the AUTODIF global variables (see the AUTODIF manual chapter on AUTODIF global variables.) The following code fragment will set these variables.

```

TOP_OF_MAIN_SECTION
arrmblsize = 200000; // use instead of
                // gradient_structure::set_ARRAY_MEMBLOCK_SIZE
gradient_structure::set_GRADSTACK_BUFFER_SIZE(100000); // this may be incorrect in
                // the AUTODIF manual.
gradient_structure::set_CMPDIF_BUFFER_SIZE(50000);
gradient_structure::set_MAX_NVAR_OFFSET(500); // can have up to 500
                // independent variables
gradient_structure::set_MAX_NUM_DEPENDENT_VARIABLES(500); // can have up to
                // 500 dependent variables

```

Note that within AD Model Builder one doesn't use the function `gradient_structure::set_ARRAY_MEMBLOCK_SIZE` to set the amount of memory available for variable arrays. Instead use the line of code `arrmblsize = nnn;` where `nnn` is the amount of memory desired.

## The GLOBALS\_SECTION

The GLOBALS\_SECTION is intended to allow the programmer to insert any desired C++ code before the main() function in the program. The code is copied literally from the template to the program. This enables the programmer to define global objects and to include include header files and user-defined functions into the generated C++ code.

## The BETWEEN\_PHASES\_SECTION

Code in the between phases section is executed before each phase of the minimization. It is possible to carry out different actions which depend on which phase of the minimization is to begin by using a `switch` statement (you can read about this in a book on C or C++) together with the `current_phase()` function.

```
switch (current_phase())
{
case 1:
    // some action
    cout << "Before phase 1 minimization " << endl;
    break;
case 2: i
    // some action
    cout << "Before phase 2 minimization " << endl;
    break;
// ....
}
```

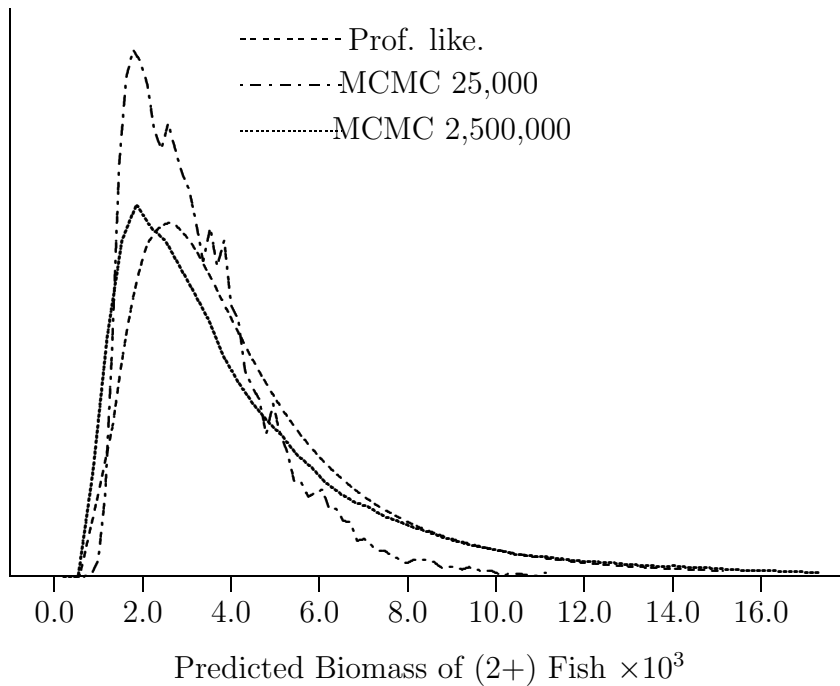
## Chapter 2

# Markov Chain Simulation

### Introduction to the Markov Chain Monte Carlo approach in Bayesian Analysis

The reference for this chapter is *Bayesian Data Analysis* (chapter 11) by Gelman *et al.*

The Markov chain Monte Carlo method (MCMC) is a method for approximating the posterior distribution for parameters of interest in the Bayesian framework. This option is invoked by using the command line option `-mcmc N` where `N` is the number of simulations performed. You will probably also want to include the option `-mcscale` which dynamically scales the covariance matrix until a reasonable acceptance rate is observed. You may also want to use the `-mcmult n` option which scales the initial covariances matrix if the initial values are so large that arithmetic errors occur. One advantage of AD Model Builder over some other implementations of MCMC is that the mode of the posterior distribution together with the hessian at the mode is available to use for the MCMC routine. This information is used to implement a version of the Hastings-Metropolis algorithm. Another advantage is that with AD Model Builder it is possible to calculate the profile likelihood for a parameter of interest and compare the distribution to the MCMC distribution for that parameter. A large discrepancy may indicate that one or both estimates are inadequate. If you wish to do more simulations (and to carry on from where the last one ended use the `-mcr` option. The following figure compares the profile likelihood for the projected biomass to the estimates produced by the MCMC method for different sample sizes (25,000 and 2,500,000 samples) for the `catage` example.



A report containing the observed distributions is produced in the file `root.hst`. All objects of type `sdreport` i.e `number`, `vector` or `matrix` are included. It is possible to save the results of every `n`'th simulation by using the `-mcsave n` option. Afterwards these values can be used by running the model with the `-mceval` option which will evaluate the `userfunction` once for every saved simulation value. At this time the function `mceval_phase()` will return the value `true` and can be used as a switch to perform desired calculations. The results are saved in a binary file `root.psv`. If you want to convert this file into ASCII see the next section. If you have a large number of variables of type `sdreport` calculating the values of them for the `mcmc` can appreciably slow down the calculations. To turn off these calculations during the `-mcsave` phase use the option `-nosdmcmc`. **Note: If you use this option and restart the `mcmc` calculations with the `-mcr` option you must use the `-nosdmcmc` as well. Otherwise the program will try to read in the non-existent histogram data.**

AD Model Builder uses the hessian to produce an (almost) multivariate normal distribution for the Metropolis-Hastings algorithm. It is not exactly multivariate normal because the random vectors produced are modified to satisfy any bounds on the parameters.

There is also an option for using a fatter tailed distribution. This distribution is a mixture of the multivariate normal and a fat-tailed distribution. It is invoked with the `-mcgrope n` option where `n` is the amount of fat-tailed distribution in the mixture. Probably a value of `n` between 0.05 and 0.10 is best.

## Reading AD Model Builder binary files

Often the data which AD Model Builder needs to save are saved in the form of a binary file using the `uistream` and `uostream` classes. If these data consist of a series of vectors all of which have the same dimension they are often saved in this form where the dimension is saved at the top of the file and the vectors are saved afterwards. It may be useful to convert these numbers into binary form so that they can be put into other programs such as spreadsheets. The following code will read the contents of these binary files. You should call the program `readbin.cpp`. It should be a simple matter to modify this program for other uses.

```
#include <fvar.hpp>
/* program to read a binary file (using ADMB's uistream and
   uostream stream classes) of vectors of length n.
   It is assumed that the size n is stored at the top of
   the file. there is no information about any many vectors
   are stored so we must check for an eof after each read
   To use the program you type:

           readbin filename
*/
void produce_comma_delimited_output(dvector& v)
{
    int i1=v.indexmin();
    int i2=v.indexmax();
    for (int i=i1;i<=i2;i++)
    {
        cout << v(i) << ",";
    }
    cout << endl;
}

main(int argc, char * argv[])
{
    if (argc < 2)
    {
        cerr << " Usage:  progname inputfilename" << endl;
        exit(1);
    }
    uistream uis = uistream(argv[1]);
    if (!uis)
    {
        cerr << " Error trying to open binary input file "
             << argv[1] << endl;
        exit(1);
    }
    int ndim;
    uis >> ndim;
    if (!uis)
    {
        cerr << " Error trying to read dimension of the vector"
             << " from the top of the file "
             << argv[1] << endl;
        exit(1);
    }
    if (ndim <=0)
    {
        cerr << " Read invalid dimension for the vector"
             << " from the top of the file "

```

```

        << argv[1] << " the number was " << ndim << endl;
    exit(1);
}

int nswitch;
cout << " 1 to see all records" << endl
    << " 2 then after the prompts  n1 and  n2 to see all" << endl
    << " records between n1 and n2 inclusive" << endl
    << " 3 to see the dimension of the vector" << endl
    << " 4 to see how many vectors there are" << endl;
cin >> nswitch;
dvector rec(1,ndim);
int n1=0;
int n2=0;
int ii=0;
switch(nswitch)
{
case 2:
    cout << " Put in the number for the first record you want to see"
        << endl;
    cin >> n1;
    cout << " Put in the number for the second record you want to see"
        << endl;
    cin >> n2;
case 1:
    do
    {
        uis >> rec;
        if (uis.eof()) break;
        if (!uis)
        {
            cerr << " Error trying to read vector number " << ii
                << " from file " << argv[1] << endl;
            exit(1);
        }
        ii++;
        if (!n1)
        {
            // comment out the one you don't want
            //cout << rec << endl;
            produce_comma_delimited_output(rec);
        }
        else
        {
            if (n1<=ii && ii<=n2)
            {
                // comment out the one you don't want
                //cout << rec << endl;
                produce_comma_delimited_output(rec);
            }
        }
    }
    while (1);
    break;
case 4:
    do
    {
        uis >> rec;

```

```

    if (uis.eof()) break;
    if (!uis)
    {
        cerr << " Error trying to read vector number " << ii
            << " from file " << argv[1] << endl;
        exit(1);
    }
    ii++;
}
while (1);
cout << " There are " << ii << " vectors" << endl;
break;
case 3:
    cout << " Dimension = " << ndim << endl;
default:
    ;
}
}
}

```

## Convergence diagnostics for MCMC analysis

A major difficulty with MCMC analysis is determining whether the chain has converged to the underlying distribution. In general it is never possible to prove that this convergence has occurred. In this section we concentrate on methods which hopefully will detect situations when convergence has not occurred.

The default MCMC method employed in AD Model Builder takes advantage of the fact that AD Model Builder can find the mode of the posterior distribution and compute the Hessian at the mode. If the posterior distribution is well approximated by a multivariate normal centered at the mode with covariance matrix equal to the inverse of the Hessian this method can be extremely efficient for many parameter problems, especially when compared to simpler methods such as the Gibbs sampler. The price one pays for this increased efficiency is that the method is not as robust as the Gibbs sampler and for some problems it will perform much more poorly than the Gibbs sampler.

As an example of this poor performance we consider a simple three parameter model developed by Vivian Haist to analyze Bowhead whale data.

The data for the model consist of total catches between 1848 and 1993 together with an estimate of the biomass in 1988 and an estimate of the change in relative biomass between 1978 and 1988.

```

DATA_SECTION
    init_vector cat(1848,1993)

PARAMETER_SECTION
    init_bounded_number k(5000,40000,1)
    init_bounded_number r(0,0.10,1)
    init_bounded_number p(0.5,1,2)
    number delta;

```

```

vector bio(1848,1994);
likeprof_number fink
!! fink.set_stepsize(.003);
!! fink.set_stepnumber(20);
sdreport_number finr
sdreport_number finp
objective_function_value f
PROCEDURE_SECTION
if (initial_params::mc_phase)
{
  cout << k << endl;
  cout << r << endl;
  cout << p << endl;
}
bio(1848)=k*p;

for (int iy=1848; iy<=1993; iy++)
{
  dvariable fpen1=0.0;
  bio(iy+1)=posfun(bio(iy)+r*bio(iy)*(1.-(bio(iy)/k)),100.0,fpen1);
  dvariable sr=1.- cat(iy)/bio(iy);
  dvariable kcat=cat(iy);
  f+=1000*fpen1;
  if(sr< 0.05)
  {
    dvariable fpen=0.;
    kcat=bio(iy)*posfun(sr,0.05,fpen);
    f+=10000*fpen;
//    cout << " kludge "<<iy <<" "<<kcat<<" "<<cat(iy)<<" "<<fpen<<endl;
  }
  bio(iy+1)-=kcat;
}
finr=r;
fink=k;
finp=p;
delta=(bio(1988)-bio(1978))/bio(1978);
f+=log(sqrt(2.*3.1415927)*500)+square(bio(1988)-7635.)/(2.*square(500));
f+=log(sqrt(2.*3.1415927)*.03)+square(delta-0.15)/(2.*square(.03));

```

This is a biomass dynamic model where the biomass is assumed to satisfy the difference equation

$$B_{i+1} = B_i + r * B_i(1 - B_i/k) - C_i(2.1)$$

For this formulation there is no guarantee that the biomass will remain positive so the `posfun` function has been used in the program to ensure that this condition will hold. This is a very “data poor” design.

The model was fit to the data and the standard MCMC analysis was performed for it. The results were compared to an MCMC analysis performed with the Gibbs sampler. It was found that the Gibbs sampler performed better.

It is not difficult to determine why the MCMC performed so poorly. the estimated covariance matrix for the parameters is shown below. To four significant figures the correlation between  $r$  and  $k$  is  $-1.0000$  Thus the hessian matrix is almost singular.

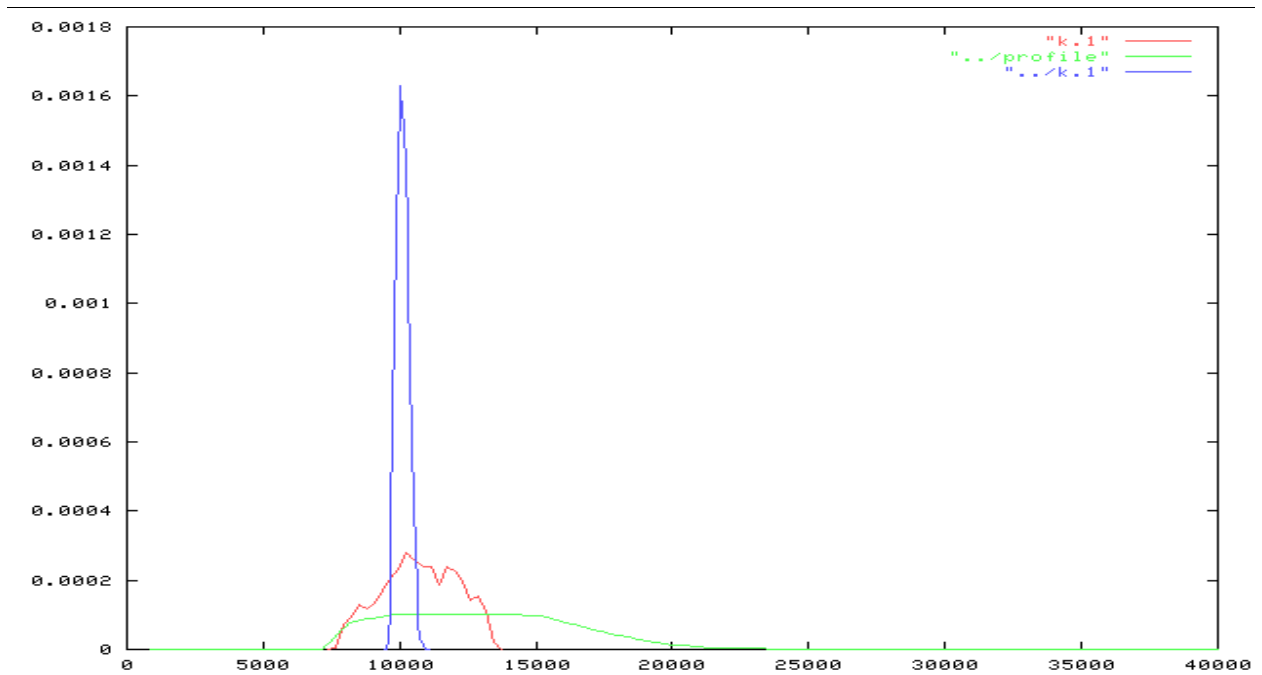
index	name	value	std dev	1	2	3
-------	------	-------	---------	---	---	---



1	k	1.0404e+04	8.8390e+05	1.0000		
2	r	4.8838e-02	9.0337e+00	-1.0000	1.0000	
3	p	5.7293e-01	3.6946e+00	0.9998	-0.9998	1.0000

If the posterior distribution were exactly normally distributed then the hessian would be constant ie not depend on the point at which is is calculated and its use would produce the most efficient MCMC procedure. However in nonlinear models the posterior distribution is not normally distributed so that the Hessian changes as we move away from the mode and the use of an almost singular Hessian can perform very badly as in the present case.

To deal with almost singular Hessians we have added the `-mcrb N` option. This option reduces the amount of correlation in the Hessian while leaving the standard deviaions fixed. The number N should be between 1 and 9. the smaller the number the more the correlation is reduced. For this example a value of 3 seemed to perform well.





## Chapter 3

# A forestry model – estimating the size distribution of wildfires

### Model description

This examples highlights two features of AD Model Builder, the use of a numerical integration routine within a statistical parameter estimation model and the use of the `ad_begin_funnel` mechanism to reduce the size of temporary file storage required. It also provides a performance comparison between AD Model Builder and Splus.

This problem investigates a model which predicts a relationship between the size and frequency of wildfires. It is assumed that the probability of observing a wildfire in size category  $i$  is given by  $P_i$ , where

$$\log(P_i) = \ln(S_i - S_{i+1}) - \ln(S(1)).$$

If  $f_i$  is the number of wildfires observed to lie in size category  $i$  the log-likelihood function for the problem is given by

$$l(\tau, \nu, \beta, \sigma) = \sum_i f_i [\ln(S_i - S_{i+1}) - \ln(S(1))] \quad (3.1)$$

where  $S_i$  is defined by the integral

$$S_i = \int_{-\infty}^{\infty} \exp\left\{-z^2/2 + \tau\left(-1 + \exp(-\nu a_i^\beta \exp(\sigma z))\right)\right\} dz \quad (3.2)$$

The parameters  $\tau$ ,  $\nu$ ,  $\beta$ , and  $\sigma$  are functions of the parameters of the original model, and don't have a simple interpretation. Fitting the model to data involves maximizing the above log-likelihood (0.1). While the gradient can be calculated (in integral form), coding it is cumbersome. Numerically maximizing the log-likelihood without specifying the gradient is preferable.

The parameter  $\beta$  is related to the fractal dimension of the perimeter of the fire. One hypothesis of interest is that  $\beta = 2/3$  which is related to hypotheses about the nature of the mechanism by which fires spread. The AD Model Builder code for the model follows.

```

DATA_SECTION
  int time0
  init_int nsteps
  init_int k
  init_vector a(1,k+1)
  init_vector freq(1,k)
  int a_index;
  number sum_freq
  !! sum_freq=sum(freq);
PARAMETER_SECTION
  init_number log_tau
  init_number log_nu
  init_number log_beta(2)
  init_number log_sigma
  sdreport_number tau
  sdreport_number nu
  sdreport_number sigma
  sdreport_number beta
  vector S(1,k+1)
  objective_function_value f
INITIALIZATION_SECTION
  log_tau 0
  log_beta -.405465
  log_nu 0
  log_sigma -2
PROCEDURE_SECTION
  tau=exp(log_tau);
  nu=exp(log_nu);
  sigma=exp(log_sigma);
  beta=exp(log_beta);
  funnel_dvariable Integral;
  int i;
  for (i=1;i<=k+1;i++)
  {
    a_index=i;
    ad_begin_funnel();
    Integral=adromb(&model_parameters::h,-3.0,3.0,nsteps);
    S(i)=Integral;
  }
  f=0.0;
  for (i=1;i<=k;i++)
  {
    dvariable ff=0.0;
    // make the model stable for case when S(i)<=S(i+1)
    // we have to subtract s(i+1) from S(i) first or roundoff will
    // do away with the 1.e-50.
    f-=freq(i)*log(1.e-50+(S(i)-S(i+1)));
    f+=ff;
  }
  f+=sum_freq*log(1.e-50+S(1));
FUNCTION dvariable h(const dvariable& z)
  dvariable tmp;
  tmp=exp(-.5*z*z + tau*(-1.+exp(-nu*pow(a(a_index),beta)*exp(sigma*z))) );

```

```

return tmp;
REPORT_SECTION
int * pt=NULL;
report << " elapsed time = " << time(pt)-time0 << " seconds" << endl;
report << "nsteps = " << setprecision(10) << nsteps << endl;
report << "f = " << setprecision(10) << f << endl;
report << "a" << endl << a << endl;
report << "freq" << endl << freq << endl;
report << "S" << endl << S << endl;
report << "S/S(1)" << endl << setfixed << setprecision(6) << S/S(1) << endl;
report << "tau " << tau << endl;
report << "nu " << nu << endl;
report << "beta " << beta << endl;
report << "sigma " << sigma << endl;

```

## The numerical integration routine

The statement

```
Integral=adromb(&model_parameters::h,-3.0,3.0,nsteps);
```

invokes the numerical integration routine for the user-defined function **h**. The function must be defined in a **FUNCTION** subsection. It can have any name, must be defined to take a **const dvariable&** argument, and must return a **dvariable**. The values -3.0, 3.0 are the limits of integration (effectively  $-\infty, \infty$  for this example). The integer argument **nsteps** determines how accurate the integration will be. Higher values of **nsteps** will be more accurate but greatly increase the amount of time necessary to fit the model. The basic strategy is to use a moderate value for **nsteps**, such as 6, and then to increase this value to see if the parameter estimates change much.

```
FUNCTION dvariable h(const dvariable& z)
```

## Using the `ad_begin_funnel` routine to reduce the amount of temporary storage required

Numerical integration routines can be very computationally intensive, especially when they must be computed to great accuracy. Such computations will require a lot of temporary storage in AD Model Builder. Fortunately the output from such a routine is just one number, the value of the integral. In automatic differentiation terminology a long set of computations which produce just one number is known as a funnel. It is possible to exploit the properties of such a funnel to greatly reduce the amount of temporary storage required. All that is necessary is to declare an object of type **funnel\_dvariable** and to assign the results of the computation to it. At the beginning of the funnel a call to the function `ad_begin_funnel` is made. There is quite a bit of overhead associated with the funnel construction so it should not be used for very small calculations. However it is possible to put it in and test

the program to see whether it runs more quickly or not. The following modified code will produce exactly the same results, but without the funnel construction.

```
dvariable Integral; // change the definition of Integral
int i;
for (i=1;i<=k+1;i++)
{
  a_index=i;
  // ad_begin_funnel(); // comment out this line
  Integral=adromb(&model_parameters::h,-3.0,3.0,nsteps);
  S(i)=Integral;
}
```

If the funnel construction is used on a portion of code which is not a funnel, incorrect derivative values will be obtained. If this is suspected the funnel should be removed as in the above example and the model run again.

## Effect of the accuracy switch on the running time for numerical integration

The following report shows the amount of time required to run the model with a fixed value of  $\beta$  for different values of the parameter `nsteps`. For practical purposes a value of `nsteps=8` gives enough accuracy so that the model could be fit in about 6 seconds.

```
elapsed time = 2 seconds nsteps = 6 f = 629.9846518
tau 9.851110 nu 8.913479 beta 0.666667 sigma 1.885570
```

```
elapsed time = 2 seconds nsteps = 7 f = 629.9851092
tau 9.850213 nu 8.835066 beta 0.666667 sigma 1.882967
```

```
elapsed time = 6 seconds nsteps = 8 f = 629.9851223
tau 9.850227 nu 8.836769 beta 0.666667 sigma 1.883024
```

```
elapsed time = 6 seconds nsteps = 9 f = 629.9851222
tau 9.850226 nu 8.836769 beta 0.666667 sigma 1.883024
```

```
elapsed time = 14 seconds nsteps = 10 f = 629.9851222
tau 9.850226 nu 8.836769 beta 0.666667 sigma 1.883024
```

The corresponding times when beta was estimated in an extra phase of the minimization are given here. It is apparent that the model parameters become unstable when beta is being estimated. Twice the log-likelihood difference is  $2(629.98 - 627.31) = 5.34$  which is significant

```
elapsed time = 3 seconds nsteps = 6 f = 627.2919906
tau 20.729183 nu 427.816375 beta 0.180225 sigma 2.499445
```

```
elapsed time = 6 seconds nsteps = 7 f = 627.2952716
tau 21.868971 nu 80914.970724 beta 0.170392 sigma 4.232237
```

```
elapsed time = 17 seconds nsteps = 8 f = 627.297021
tau 22.858629 nu 2326271883.421848 beta 0.164749 sigma 7.653068
```

```
elapsed time = 62 seconds nsteps = 9 f = 627.2993787
tau 23.771061 nu 1652877622661391616.000000 beta 0.161073 sigma 14.451510
```

```
elapsed time = 123 seconds nsteps = 10 f = 627.3106333
tau 23.116097 nu 49753858778.636856 beta 0.159364 sigma 8.663666
```

```
elapsed time = 244 seconds nsteps = 11 f = 627.310624
tau 23.115275 nu 49009470510.133156 beta 0.159369 sigma 8.658643
```

## A comparison with Splus for the forestry model

The Splus minimizing routine `nlminb` was used to fit the model. Fitting the three parameter model with Splus required approximately 280 seconds compared to 6 seconds with AD Model Builder, so that AD Model Builder was approximately 45 times faster for this simple problem.

For the four parameter problem with beta estimated, the SPLUS routine exited after fourteen minutes and 30 seconds, reporting false convergence with a function value of 627.338.

The data for the example is

```
a
0.04 0.1 0.2 0.4 0.8 1.6 3.2 6.4 12.8 25.6 51.2 102.4 204.8
freq
167 84 61 29 19 17 4 4 1 0 1 1
```

where the first line contains the bounds for the size categories and the second line contains the number of observations in each size category. The Splus code with fixed beta for the example is

```
obj.20<-
function(xvec)
{
#Objective for maxn in NLMINB NB vector argument
- llik.20(xvec[1], xvec[2], xvec[3])
}
llik.20<-
function(logtau, lognu, logsigma)
{
    tau<-exp(logtau)
    nu<-exp(lognu)
    sigma<-exp(logsigma)
print(tau)
print(nu)
print(sigma)
    llik <- 0
    for(i in 1:(length(freq)+1)) {
        Int[i]<-S.20(xa[i], tau, nu, sigma)
    }
    print(llik)
    for(i in 1:length(freq)) {
```

```

        llik <- llik + (freq[i] * (log(1.e-50+(Int[i]-Int[i+1]))
        -log(1.e-50+Int[1])))
    }
    llik
}
S.20<-
function(da, tau, nu, sigma)
{
    results <- integrate(intgnd.20, -3, 3, TAU = tau, NU = nu, SIGMA =
        sigma, A = da)
    if(results$message != "normal termination")
        ans <- results$message
    else ans <- results$integral
    ans
}
intgnd.20<-
function(z, A, TAU, NU, SIGMA)
{

exp(- 0.5 * z2 + TAU * (-1 + exp(- NU * A2/3 * exp(SIGMA * z))))

}

```

To run the example in Splus with the same initial values use the following values

```
logtau 0 lognu 0 logsigma -2
```

The vector xa should contain the 13 a values while the vector freq should contain the 12 observed frequencies.



## Chapter 4

# Economic Models – regime switching

An active field in macroeconomic modeling is the area of “regime switching”. This is discussed in greater generality in Hamilton (1994, chapter 22)<sup>1</sup>. The code for the following example is based on the domain switching model taken from Hamilton (1989)<sup>2</sup>. This example is not ideal for exploiting AD Model Builder’s greatest advantage, the ability to estimate parameters in models with a large number of independent variables. However it does illustrate the efficacy of the use of higher (up to seven dimensional) arrays in AD Model Builder.

### Analysis of economic data from Hamilton’s 1989 paper

For this model The observed quantities are the  $Y_t$  where

$$Y_t = a_0 + a_1 s_{ti} + Z_t \quad (4.1)$$

and the state variables  $Z_t$  satisfy the fourth order autoregressive relationship

$$Z_t = f_1 Z_{t-1} + f_2 Z_{t-2} + f_3 Z_{t-3} + f_4 Z_{t-4} + \epsilon_t \quad (4.2)$$

where the  $\epsilon_t$  are independent, normally distributed random variables with mean 0 and standard deviation  $\sigma$ . These equations correspond to Hamilton’s equations 4.3. The state variable  $s_{ti}$  is the realized value of a Markov process,  $S_t$ , whose evolution is described below. This coefficient takes on the value  $i$  when the system is in state  $i$ . In the current example there are two states so that  $s_t$  takes on one of the two values 0 or 1. We can solve 0.1 for the values of  $Z_t$  conditioned on the unknown value of the state at time  $t$ . Let  $z_{ti}$  be defined by

$$\begin{aligned} z_{i0} &= Y_t - a_0 \\ z_{t1} &= Y_t - a_0 - a_1 \end{aligned}$$

---

<sup>1</sup>Hamilton, James D. 1994. *Time Series Analysis*, Princeton, N.J.: Princeton University Press.

<sup>2</sup>A new approach to the economic analysis of nonstationary time series and the business cycle, *Econometrica*, **57(2)**:357-384.

$$(4.3)$$

Let  $(i, j, k, l, m)$  be a quintuplet of state values for the states at time  $t, t - 1, \dots, t - 4$ . Define  $e(t, i, j, k, l, m)$ , the realized values of the random variables  $\epsilon_t$  by

$$e(t, i, j, k, l, m) = Y_{ti} - f_1 z_{t-1, j} - f_2 z_{t-2, k} - f_3 z_{t-3, l} - f_4 z_{t-4, m}$$

Notice that we due to the lags we can only begin to calculate values for the  $e(t, i, j, k, l, m)$  in time period 5. It is assumed that the states transitions are given by a Markov process with transition matrix  $P = (p_{ij})^3$  If we are in state  $j$  at time  $t$  the probability of being in state  $i$  at time  $t + 1$  is  $p_{ij}$ .

If we consider the quintuple of the last 5 states to be the states of a new markov process then we can define the transition matrix for this process by

$$(i, j, k, l, m) \Rightarrow (0, i, j, k, l) \quad \text{with probability } p_{0i}$$

and

$$(i, j, k, l, m) \Rightarrow (1, i, j, k, l) \quad \text{with probability } p_{1i}$$

If  $q(t - 1, j, k, l, m, n)$  is the probability of being in state  $(j, k, l, m, n)$  at period  $t - 1$  the probability of being in state  $q(t, i, j, k, l, m)$  at time period  $t$  is given by

$$q(t, i, j, l, , m) = \sum_n P_{ij} q(t - 1, j, k, l, m, n)$$

In particular if

$$q_b(t, i, j, k, l, m)$$

is the probability of being in the state  $(i, j, l, m, n)$  before observing  $Y_t$  and  $q_a(t - 1, j, k, l, m, n)$  is the probability of being in the state  $(j, k, l, m, n)$  after observing  $Y_{t-1}$  then

$$q_b(t, i, j, k, l, m) = \sum_n P_{ij} q_a(t - 1, j, k, l, m, n) \quad (4.4)$$

Let  $Q(Y_t | (i, j, k, l, m), Y_{t-1}, Y_{t-2}, Y_{t-3}, Y_{t-4})$  be the conditional probability (or probability density) for  $Y_t$  given  $S_t = i, S_{t-1} = j, S_{t-2} = k, S_{t-3} = l, S_{t-4} = m, Y_{t-1}, Y_{t-2}, Y_{t-3}, Y_{t-4}$ . Then, ignoring a constant term which is irrelevant for the calculations,

$$Q(Y_t | (i, j, k, l, m), Y_{t-1}, Y_{t-2}, Y_{t-3}, Y_{t-4}) = \exp(-e(i, j, k, l, m)^2 / 2\sigma^2) / \sigma \quad (4.5)$$

Define  $u(Y_t, i, j, k, l, m)$  by

$$u(Y_t, i, j, k, l, m) = \frac{Q(Y_t | (i, j, k, l, m), Y_{t-1}, \dots, Y_{t-4}) q_b(t, i, j, k, l, m)}{\quad} \quad (4.6)$$

<sup>3†††</sup>Hamilton seems to index his matrices with the column index first in some cases. We use the row index first. Thus Hamilton's  $p_{ij}$  may correspond to our  $p_{ji}$ .

Then  $q_a(t, i_t, j, k, l, m)$  can be calculated from the relationship

$$q_a(t, i_t, j, k, l, m) = u(Y_t, i, j, k, l, m) / \sum_{i,j,k,l,m} u(Y_t, i, j, k, l, m) \quad (4.7)$$

The log-likelihood function for the parameters can be calculated from the  $u(Y_t, i, j, k, l, m)$ . It is equal to

$$\sum_t \log(\sum_{i,j,k,l,m} u(Y_t, i, j, k, l, m)) \quad (4.8)$$

The sums needed for the calculations in 0.9 can be saved from the calculations for 0.8).

## The code for Hamilton's fourth order autoregressive model

The complete AD Model Builder template (TPL) code is in the file `ham4.tpl` The C++ (CPP) code produced from this is in the file `ham4.cpp` Here is the TPL code split up with comments.

```
DATA_SECTION
  init_number a1init // read in the initial value of a1 with the data
  init_int nperiods1 // the number of observations
  int nperiods // nperiods-1 after differencing
  !! nperiods=nperiods1-1;
  init_vector yraw(1,nperiods1) //read in the observations
  vector y(1,nperiods) // the differenced observations
  !! y=100.*(--log(yraw(2,nperiods1)) - log(yraw(1,nperiods)));
  int order
  int op1
  !! order=4; //order of the autoregressive process
  !! op1=order+1;
  int nstates // the number of states (expansion and contraction)
  !! nstates=2;
```

The `DATA_SECTION` contains constant quantities or “data”. This is in contrast to quantities which depend on parameters being estimated which go into the `PARAMETER_SECTION`. All quantities in the `PARAMETER_SECTION` with the `init_` prefix are initial data which must be read in from somewhere. By default they are read in from the file `ROOT.dat` (DAT file) where `ROOT` is the root part of the name of the program being run (in this case `ham4.exe`), so `ham4.dat`.

The first quantity is a number, `a1init` which will be used for initializing the value of `a1` in the program. This is a simple way to try different initial values for `a1` simply by modifying the input data file. Such procedures are often valuable to ensure that the correct global value of the objective function has been found. The second quantity `nperiods1` is the number of data points in the file. Notice that as soon as a quantity has been defined it is available to use for defining other quantities. The quantity `nperiod` does not have an `init_` before it so it will not be read in an must be calculated in terms of other quantities at some point. Since we want it now it is calculated immediately.

```
!! nperiods=nperiods1-1;
```

The `!!` are used to insert any valid C++ code into the `DATA_SECTION` or `PARAMETER_SECTION` (see `LOCAL_CALC`s). This code will be executed verbatim (after the `!!` have been stripped off of course) at the appropriate time. The `init_vector yraw` is defined and give a size with indices going from 1 to `nperiods1`. The `nperiods1` data points will be read into `yraw` from the DAT file. The data are immediately transformed and the resulting `nperiods` data point are put into `y`.

```
PARAMETER_SECTION
  init_vector f(1,order,1) // coefficients for the autoregressive
                        // process
  init_bounded_matrix Pcoeff(0,nstates-1,0,nstates-1,.01,.99,2)
    // determines the transition matrix for the markov process
  init_number a0(5) // equation 4.3 in Hamilton (1989)
  init_bounded_number a1(0.0,10.0,4);
  !! if (a0==0.0) a1=a1init; // set initial value for a1 as specified
                        // in the top of the file nham4.dat
  init_bounded_number smult(0.01,1,3) // used in computing sigma
  matrix z(1,nperiods,0,1) // computed via equation 4.3 in
                        // Hamilton (1989)
  matrix qbefore(op1,nperiods,0,1); // prob. of being in state before
  matrix qafter(op1,nperiods,0,1); // and after observing y(t)
  number sigma // variance of epsilon(t) in equation 4.3
  number var // square of sigma
  sdreport_matrix P(0,nstates-1,0,nstates-1);
  number ff1;
  vector qb1(0,1);
  matrix qb2(0,1,0,1);
  3darray qb3(0,1,0,1,0,1);
  4darray qb4(0,1,0,1,0,1,0,1);
  6darray qb(op1,nperiods,0,1,0,1,0,1,0,1,0,1);
  6darray qa(op1,nperiods,0,1,0,1,0,1,0,1,0,1);
  6darray eps(op1,nperiods,0,1,0,1,0,1,0,1,0,1);
  6darray eps2(op1,nperiods,0,1,0,1,0,1,0,1,0,1);
  6darray prob(op1,nperiods,0,1,0,1,0,1,0,1,0,1);
  objective_function_value ff;
```

The `PARAMETER_SECTION` describes the parameters of the model, that is, the quantities to be estimated. Quantities which have the prefix `init_` are akin to the independent variables from which the log-likelihood function (or more generally any objective function) can be calculated. Other objects are dependent variables which must be calculated from the independent variables. The default behaviour of AD Model Builder is to read in initial parameter values for the parameters from a `PAR` file if it finds one. Otherwise they are given default values consistent with their type. The quantity `f` is a vector of four coefficients for the autoregressive process. `Pcoeff` is a  $2 \times 2$  matrix which is used to parameterize The transition matrix `P` for the Markov process. Its values are restricted to lie between .01 and 0.99. `smult` is a number used to parameterize `sigma` and `var` (which is the variance) as a multiple of the mean squared residuals. This reparameterization undimensionalizes the calculation and is a good technique to employ for nonlinear modeling in general. The transition matrix `P` is defined to be of type `sdreport_matrix` so that the standard deviation estimates for its members will be included in the standard deviation report contained in the `STD` file. To date AD Model Builder supports up to seven dimensional arrays. For historical reasons one and

two dimensional arrays are referred to as **vector** and **matrix**. This becomes a bit difficult for higher dimensional arrays so they are simply referred to as **3darray**, **4darray**, ..., **7darray**.

```

PROCEDURE_SECTION
P=Pcoeff;
dvar_vector ssum=colsum(P); // form a vector whose elements are the
                          // sums of the columns of P
ff+=norm2(log(ssum)); // this is a penalty so that the hessian will
                      // not be singular and the coefficients of P
                      // will be well defined
// normalize the transition matrix P so its columns sum to 1
int j;
for (j=0;j<=nstates-1;j++)
{
  for (int i=0;i<=nstates-1;i++)
  {
    P(i,j)/=ssum(j);
  }
}

// get z into a useful format
dvar_matrix ztrans(0,1,1,nperiods);
ztrans(0)=y-a0;
ztrans(1)=y-a0-a1;
z=trans(ztrans);
int t,i,k,l,m,n;

qb1(0)=(1.0-P(1,1))/(2.0-P(0,0)-P(1,1)); // unconditional distribution
qb1(1)=1.0-qb1(0);

// for periods 2 through 4 there are no observations to condition
// the state distributions on so we use the unconditional distributions
// obtained by multiplying by the transition matrix P.
for (i=0;i<=1;i++) {
  for (j=0;j<=1;j++) qb2(i,j)=P(i,j)*qb1(j);
}

for (i=0;i<=1;i++) {
  for (j=0;j<=1;j++) {
    for (k=0;k<=1;k++) qb3(i,j,k)=P(i,j)*qb2(j,k);
  }
}

for (i=0;i<=1;i++) {
  for (j=0;j<=1;j++) {
    for (k=0;k<=1;k++) {
      for (l=0;l<=1;l++) qb4(i,j,k,l)=P(i,j)*qb3(j,k,l);
    }
  }
}

// qb(5) is the probability of being in one of 32
// states (32=2x2x2x2x2) in periods 5,4,3,2,1 before observing
// y(5)
for (i=0;i<=1;i++) {
  for (j=0;j<=1;j++) {

```

```

    for (k=0;k<=1;k++) {
      for (l=0;l<=1;l++) {
        for (m=0;m<=1;m++) qb(op1,i,j,k,l,m)=P(i,j)*qb4(j,k,l,m);
      }
    }
  }
}
// now calculate the realized values for epsilon for all
// possible combinations of states
for (t=op1;t<=nperiods;t++) {
  for (i=0;i<=1;i++) {
    for (j=0;j<=1;j++) {
      for (k=0;k<=1;k++) {
        for (l=0;l<=1;l++) {
          for (m=0;m<=1;m++) {
            eps(t,i,j,k,l,m)=z(t,i)-phi(z(t-1,j),
              z(t-2,k),z(t-3,l),z(t-4,m),f);
            eps2(t,i,j,k,l,m)=square(eps(t,i,j,k,l,m));
          }
        }
      }
    }
  }
}
// calculate the mean squared "residuals" for use in
// "undimensionalized" parameterization of sigma
dvariable eps2sum=sum(eps2);
var=smult*eps2sum/(32.0*(nperiods-4));
sigma=sqrt(var);

for (t=op1;t<=nperiods;t++) {
  for (i=0;i<=1;i++) {
    for (j=0;j<=1;j++) {
      for (k=0;k<=1;k++)
        prob(t,i,j,k)=exp(eps2(t,i,j,k)/(-2.*var))/sigma;
    }
  }
}

for (i=0;i<=1;i++) {
  for (j=0;j<=1;j++) {
    for (k=0;k<=1;k++) {
      for (l=0;l<=1;l++) {
        for (m=0;m<=1;m++) qa(op1,i,j,k,l,m)= qb(op1,i,j,k,l,m)*
          prob(op1,i,j,k,l,m);
      }
    }
  }
}
}
ff1=0.0;
qbefore(op1,0)=sum(qb(op1,0));
qbefore(op1,1)=sum(qb(op1,1));
qafter(op1,0)=sum(qa(op1,0));
qafter(op1,1)=sum(qa(op1,1));
dvariable sumqa=sum(qaafter(op1));
qa(op1)/=sumqa;
qafter(op1,0)/=sumqa;
qafter(op1,1)/=sumqa;

```

```

ff1=-log(1.e-50+sumqa);
for (t=op1+1;t<=nperiods;t++) { // notice that the t loop includes 2
  for (i=0;i<=1;i++) { // i,j,k,l,m blocks
    for (j=0;j<=1;j++) {
      for (k=0;k<=1;k++) {
        for (l=0;l<=1;l++) {
          for (m=0;m<=1;m++) {
            qb(t,i,j,k,l,m).initialize();
            // here is where having 6 dimensional arrays makes the
            // formula for moving the state distributions from period
            // t-1 to period t easy to program and understand.
            // Throw away n and accumulate its two values into next
            // time period after multiplying by transition matrix P
            for (n=0;n<=1;n++) qb(t,i,j,k,l,m)+=P(i,j)*qa(t-1,j,k,l,m,n);
          }
        }
      }
    }
  }
  for (i=0;i<=1;i++) {
    for (j=0;j<=1;j++) {
      for (k=0;k<=1;k++) {
        for (l=0;l<=1;l++) {
          for (m=0;m<=1;m++) qa(t,i,j,k,l,m)=qb(t,i,j,k,l,m)*
            prob(t,i,j,k,l,m);
        }
      }
    }
  }
  }
  qbefore(t,0)=sum(qb(t,0));
  qbefore(t,1)=sum(qb(t,1));
  qafter(t,0)=sum(qa(t,0));
  qafter(t,1)=sum(qa(t,1));
  dvariable sumqa=sum(qaafter(t));
  qa(t)/=sumqa;
  qafter(t,0)/=sumqa;
  qafter(t,1)/=sumqa;
  ff1=-log(1.e-50+sumqa); // add small constant to avoid log(0)
}
ff+=ff1; //ff1 is minus the log-likelihood
ff+=.1*norm2(f); // add small penalty to stabilize estimation

```

The PROCEDURE\_SECTION is where the calculation of the objective function are carried out. First the transition matrix P is calculated from the Pcoeff. The function colsum forms a vector whose elements are the column sums of the matrix. This is used to normalize P so that its columns sum to 1. A penalty is added to the objective function for the column sums so that the hessian matrix with respect to the independent variables will not be singular. This does not affect the “statistical” properties of the parameters of interest. The matrix z is calculated using a transformed matrix because AD Model Builder deals with vector rows better than columns. The probability distribution for the states in period 1, qb1 is set equal to the unconditional distribution for a Markov process in terms of its transition matrix, P, as discussed in Hamilton (1994). The transition matrix is used to compute the probability distribution of the states in periods (2, 1), (3, 2, 1), (4, 3, 2, 1), and finally (5, 4, 3, 2, 1). For the last quintuplet this is the probability distribution before observing y(5). The quantities

`eps` in the code correspond to the possible realized values of the random variable  $\epsilon$ . The quantities `qa` and `qb` correspond to  $q_a$  and  $q_b$  in the documentation. The `sum` function is defined for arrays of any dimension and simply forms the sum of all the components. In AD Model Builder if `xx` is an  $n$  dimensional array then `x(i)` is an  $n-1$  dimensional array. So the statement

```
qbefore(t,0)=sum(qb(t,0));
```

takes the sum of the probabilities for the sixteen quintuples of states at time period `t` through `t-4` for which the state at time period `t` is 0. These are used in the `REPORT_SECTION` to write out a report of the estimated state probabilities at time period `t` before and after observing `y(t)`.

```
REPORT_SECTION
dvar_matrix out(1,2,op1,nperiods);
dvar_matrix out1(1,1,op1,nperiods);
out(1)=trans(qbefore)(1);
out(2)=trans(qafter)(1);
{
  ofstream ofs("qbefore.rep");
  out1(1)=trans(qbefore)(0);
  ofs << trans(out1)<< endl;
}
{
  ofstream ofs("qafter.rep");
  out1(1)=trans(qafter)(0);
  ofs << trans(out1) << endl;
}
report << "#qbefore   qafter" << endl;
report << setfixed << setprecision(3) << setw(7) << trans(out) << endl;
```

The `REPORT_SECTION` is used to report any result in a manner not already carried out by the models default behaviour. The probabilities of being in state 0 before and after observing `y(t)` are printed into the files `qbefore.rep` and `qafter.rep`. These vectors were stored in files so that they could be easily imported into graphing programs. The results are very similar to figure 1 in Hamilton (1989) as one might hope.

```
RUNTIME_SECTION
maximum_function_evaluations 20000
convergence_criteria 1.e-6
```

The `maximum_function_evaluations 20000` will simply let the program run a long time by setting the maximum number of function evaluations in the function minimizer equal to 20,000 (nowhere near this many are actually needed.) The `convergence_criteria 1.e-6` was needed because the default value of `1.e-4` caused the program to exit from the minimization before convergence had been achieved.

```
TOP_OF_MAIN_SECTION
arrmblsize=500000;
gradient_structure::set_GRADSTACK_BUFFER_SIZE(200000);
gradient_structure::set_CMPDIF_BUFFER_SIZE(2100000);
```



The `TOP_OF_MAIN_SECTION` is for including code which will be included at the top of the `main()` function in the C++ program. Any desired legal code may be included. There are a number of common statements which are used to control aspects of AD Model Builder's performance. The statement `arrmblsize=500000;` reserves 500,000 bytes of memory for variable objects. If it is not large enough a message will be printed out at run time. See the index for references to more discussion of this matter. The statements `gradient_structure::set_GRADSTACK_BUFFER_SIZE(200000);` and `gradient_structure::set_CMPDIF_BUFFER_SIZE(2100000);` set the amount of memory that AD Model Builder reserves for variable objects. Setting these is a matter of tuning for optimum performance. If you have a lot of memory available making them larger may improve performance. However models will run without including these statements as long as there is enough memory for AD Model Builder's temporary files.

```

GLOBALS_SECTION
#include <admodel.h>

dvariable phi(const dvariable& a1,const dvariable& a2,const dvariable& a3,
              const dvariable& a4,const dvar_vector& f)
{
    return    a1*f(1)+a2*f(2)+a3*f(3)+a4*f(4);
}

```

The `GLOBALS_SECTION` is used to include statements at the top of the file containing the CPP program. This is generally where global declarations are made in C++, hence its name. However it may be used for any legal statements such as including header files for the users data structures etc. In this case it has been used to define the function `phi` which is used to simplify the code for the model's calculations. The header file `admodel.hpp` is included to define the `AUTODIF` structures used in the definition of the function. This header is automatically included near the top of the file, but this would be too late as `GLOBALS_SECTION` material is included first.

## Results of the analysis

The parameter estimates for the initial parameters are written into a file `HAM4.PAR`. This is an ASCII file which can be easily read. (The results are also stored in a binary file `HAM4.BAR` which can be used to restart the model with more accurate parameters estimates.)

```

# Objective function value = 60.8934
# f:
0.0139989 -0.0569580 -0.246292 -0.212250
# Pcoeff:
0.754133 0.0955834
0.245118 0.900333
# a0:
-0.357964
# a1:
1.52138

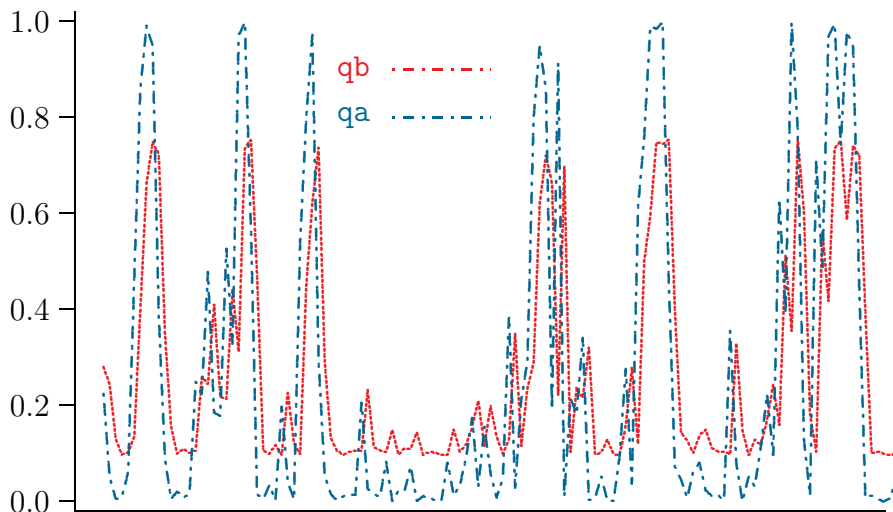
```

```
# smult:  
0.281342
```

The estimates are almost identical to those reported in Hamilton (1989)<sup>4</sup> The first line reports the value of the log-likelihood function. This value can be used in hypothesis (likelihood-ratio) tests. the file `ham5.para` for the fifth order autoregressive model fit to the data in Hamilton (1989) is shown below. there is one more parameter in this model. Twice the difference in the log-likelihood functions is  $2(60.89 - 59.60) = 2.58$ . For one extra parameter the 95% significance level is 3.84, the improvement in fit is not significant.

```
# Objective function value = 59.6039  
# f:  
-0.0474771 -0.113829 -0.241966 -0.225535 -0.192585  
# Pcoeff:  
0.779245 0.0951739  
0.219775 0.900719  
# a0:  
-0.271318  
# a1:  
1.46301  
# smult:  
0.259541
```

The plot of `qa` and `qb` demonstrates the extra information about the probability distribution of the current state contained in in the current value of  $y(t)$ .



Apriori and aposteriori Probabilites of Being in State 0 in Period t

---

<sup>4</sup>Our method for parameterizing the initial state probability distribution `qb1` is slightly different from Hamilton's which would explain the small discrepancy.

The standard deviation and correlation report for the model are in the file `ham4.cor` reproduced below.

```

index name  value  std dev  1  2  3  4  5  6  7  8  9  10  11  12  13  14  15
1  f      1.39e-02  1.20e-01  1.00
2  f      -5.69e-02  1.37e-01  0.33  1.00
3  f      -2.46e-01  1.06e-01  0.33  0.29  1.00
4  f      -2.12e-01  1.10e-01  0.43  0.26  0.17  1.00
5  Pcoeff  7.54e-01  5.39e-01  0.00  0.04  0.01  0.00  1.00
6  Pcoeff  9.55e-02  7.58e-02  0.04  0.05  0.02  0.03 -0.04  1.00
7  Pcoeff  2.45e-01  1.97e-01 -0.01 -0.11 -0.03 -0.01  0.77  0.04  1.00
8  Pcoeff  9.00e-01  6.20e-01 -0.00 -0.00 -0.00 -0.00  0.00  0.83 -0.00  1.00
9  a0     -3.57e-01  2.65e-01  0.27  0.56  0.25  0.21  0.08  0.07 -0.23 -0.00  1.00
10 a1     1.52e+00  2.63e-01 -0.31 -0.57 -0.29 -0.25 -0.07 -0.04  0.21  0.00 -0.96  1.00
11 smult  2.81e-01  1.25e-01  0.54  0.69  0.48  0.45  0.06  0.05 -0.17 -0.00  0.82 -0.84  1.00
12 P      7.54e-01  9.65e-02  0.02  0.24  0.07  0.03  0.17 -0.08 -0.48  0.00  0.47 -0.44  0.36  1.00
13 P      9.59e-02  3.77e-02  0.09  0.10  0.04  0.06 -0.02  0.49  0.08 -0.05  0.14 -0.09  0.11 -0.16  1.00
14 P      2.45e-01  9.65e-02 -0.02 -0.24 -0.07 -0.03 -0.17  0.08  0.48 -0.00 -0.47  0.44 -0.36 -1.00  0.16  1.00
15 P      9.04e-01  3.77e-02 -0.09 -0.10 -0.04 -0.06  0.02 -0.49 -0.08  0.05 -0.14  0.09 -0.11  0.16 -1.00 -0.16  1.00

```

## Extending Hamilton's model to a fifth order autoregressive process

Hamilton (1989, page 372) remarks that investigating higher order autoregressive processes might be a fruitful area of research. The form of the model is. The first extension of the model is a fifth order autoregressive process.

$$Y_t = a_0 + a_1 s_{ti} + Z_t \quad (4.9)$$

and the state variables  $Z_t$  satisfy the fourth order autoregressive relationship

$$Z_t = f_1 Z_{t-1} + f_2 Z_{t-2} + f_3 Z_{t-3} + f_4 Z_{t-4} + f_5 Z_{t-5} + \epsilon_t \quad (4.10)$$

which extend equations 0.1 and 0.2. The TPL file `ham5.tpl` for the fifth order autoregressive model is reproduced here. By employing higher dimensional arrays the conversion of the TPL file from a fourth order autoregressive process to a fifth order one is largely formal. An experienced AD Model Builder user can carry out the modifications in under 1 hour. Places where modifications were made were tagged with the comment `tt //!!5`.

DATA\_SECTION

```

init_number a1init // read in the initial value of a1 with the data
init_int nperiods1 // the number of observations
int nperiods // nperiods-1 after differencing
!! nperiods=nperiods1-1;
init_vector yraw(1,nperiods1) //read in the observations
vector y(1,nperiods) // the differenced observations
!! y=100.*(--log(yraw(2,nperiods1)) - log(yraw(1,nperiods)));
int order
int op1
!! order=5; // !!5 order of the autoregressive process
!! op1=order+1;
int nstates // the number of states (expansion and contraction)
!! nstates=2;
PARAMETER_SECTION
init_vector f(1,order,1) // coefficients for the autoregressive
// process
init_bounded_matrix Pcoeff(0,nstates-1,0,nstates-1,.01,.99,2)
// determines the transition matrix for the markov process
init_number a0(5) // equation 4.3 in Hamilton (1989)
init_bounded_number a1(0.0,10.0,4);
!! if (a0==0.0) a1=a1init; // set initial value for a1 as specified
// in the top of the file nham4.dat
init_bounded_number smult(0.01,1,3) // used in computing sigma
matrix z(1,nperiods,0,1) // computed via equation 4.3 in
// Hamilton (1989)
matrix qbefore(op1,nperiods,0,1); // prob. of being in state before
matrix qafter(op1,nperiods,0,1); // and after observing y(t)
number sigma // variance of epsilon(t) in equation 4.3
number var // square of sigma
sdreport_matrix P(0,nstates-1,0,nstates-1);
number ff1;
vector qb1(0,1);
matrix qb2(0,1,0,1);
3darray qb3(0,1,0,1,0,1);
4darray qb4(0,1,0,1,0,1,0,1);
5darray qb5(0,1,0,1,0,1,0,1,0,1); // !!5
7darray qb(op1,nperiods,0,1,0,1,0,1,0,1,0,1,0,1);
7darray qa(op1,nperiods,0,1,0,1,0,1,0,1,0,1,0,1);
7darray eps(op1,nperiods,0,1,0,1,0,1,0,1,0,1,0,1);
7darray eps2(op1,nperiods,0,1,0,1,0,1,0,1,0,1,0,1);
7darray prob(op1,nperiods,0,1,0,1,0,1,0,1,0,1,0,1);
objective_function_value ff;
PROCEDURE_SECTION
P=Pcoeff;
dvar_vector ssum=colsum(P); // forma a vector whose elements are the
// sums of the columns of P
ff+=norm2(log(ssum)); // this is a penalty so that the hessian will
// not be singular and the coefficients of P
// will be well defined
// normalize the transition matrix P so its columns sum to 1
int j;
for (j=0;j<=nstates-1;j++)
{
for (int i=0;i<=nstates-1;i++)
{
P(i,j)/=ssum(j);
}
}
}

```

```

dvar_matrix ztrans(0,1,1,nperiods);
ztrans(0)=y-a0;
ztrans(1)=y-a0-a1;
z=trans(ztrans);
int t,i,k,l,m,n,p;

qb1(0)=(1.0-P(1,1))/(2.0-P(0,0)-P(1,1)); // unconditional distribution
qb1(1)=1.0-qb1(0);

// for periods 2 through 4 there are no observations to condition
// the state distributions on so we use the unconditional distributions
// obtained by multiplying by the transition matrix P.
for (i=0;i<=1;i++) {
  for (j=0;j<=1;j++) qb2(i,j)=P(i,j)*qb1(j);
}

for (i=0;i<=1;i++) {
  for (j=0;j<=1;j++) {
    for (k=0;k<=1;k++) qb3(i,j,k)=P(i,j)*qb2(j,k);
  }
}

for (i=0;i<=1;i++) {
  for (j=0;j<=1;j++) {
    for (k=0;k<=1;k++) {
      for (l=0;l<=1;l++) qb4(i,j,k,l)=P(i,j)*qb3(j,k,l);
    }
  }
}

// !!5
for (i=0;i<=1;i++) {
  for (j=0;j<=1;j++) {
    for (k=0;k<=1;k++) {
      for (l=0;l<=1;l++) {
        for (m=0;m<=1;m++) qb5(i,j,k,l,m)=P(i,j)*qb4(j,k,l,m);
      }
    }
  }
}

// qb(6) is the probability of being in one of 64
// states (64=2x2x2x2x2x2) in periods 5,4,3,2,1 before observing
// y(6)
for (i=0;i<=1;i++) {
  for (j=0;j<=1;j++) {
    for (k=0;k<=1;k++) {
      for (l=0;l<=1;l++) {
        for (m=0;m<=1;m++) { // !!5
          for (n=0;n<=1;n++) qb(op1,i,j,k,l,m,n)=P(i,j)*qb5(j,k,l,m,n);
        }
      }
    }
  }
}

// now calculate the realized values for epsilon for all
// possible combinations of states
for (t=op1;t<=nperiods;t++) {
  for (i=0;i<=1;i++) {
    for (j=0;j<=1;j++) {

```

```

    for (k=0;k<=1;k++) {
      for (l=0;l<=1;l++) {
        for (m=0;m<=1;m++) {
          for (n=0;n<=1;n++) { // !!5
            eps(t,i,j,k,l,m,n)=z(t,i)-phi(z(t-1,j),
              z(t-2,k),z(t-3,l),z(t-4,m),z(t-5,n),f);
            eps2(t,i,j,k,l,m,n)=square(eps(t,i,j,k,l,m,n));
          }
        }
      }
    }
  }
}

// calculate the mean squared "residuals" for use in
// "undimensionalized" parameterization of sigma
dvariable eps2sum=sum(eps2);
var=smult*eps2sum/(64.0*(nperiods-4)); //!!5
sigma=sqrt(var);

for (t=op1;t<=nperiods;t++) {
  for (i=0;i<=1;i++) {
    for (j=0;j<=1;j++) {
      for (k=0;k<=1;k++) {
        for (l=0;l<=1;l++) //!!5
          prob(t,i,j,k,l)=exp(eps2(t,i,j,k,l)/(-2.*var))/sigma;
      }
    }
  }
}

for (i=0;i<=1;i++) {
  for (j=0;j<=1;j++) {
    for (k=0;k<=1;k++) {
      for (l=0;l<=1;l++) {
        for (m=0;m<=1;m++) {
          for (n=0;n<=1;n++) qa(op1,i,j,k,l,m,n)= qb(op1,i,j,k,l,m,n)*
            prob(op1,i,j,k,l,m,n);
        }
      }
    }
  }
}

ff1=0.0;
qbefore(op1,0)=sum(qb(op1,0));
qbefore(op1,1)=sum(qb(op1,1));
qafter(op1,0)=sum(qa(op1,0));
qafter(op1,1)=sum(qa(op1,1));
dvariable sumqa=sum(qaafter(op1));
qa(op1)/=sumqa;
qafter(op1,0)/=sumqa;
qafter(op1,1)/=sumqa;
ff1-=log(1.e-50+sumqa);
for (t=op1+1;t<=nperiods;t++) { // notice that the t loop includes 2
  for (i=0;i<=1;i++) { // i,j,k,l,m blocks
    for (j=0;j<=1;j++) {
      for (k=0;k<=1;k++) {
        for (l=0;l<=1;l++) {

```

```

        for (m=0;m<=1;m++) {
            for (n=0;n<=1;n++) { ///!!5
                qb(t,i,j,k,l,m,n).initialize();
                // here is where having 6 dimensional arrays makes the
                // formula for moving the state distributions form period
                // t-1 to period t easy to program and understand.
                // Throw away n and accumulate its two values into next
                // time period after multiplying by transition matrix P
                for (p=0;p<=1;p++) qb(t,i,j,k,l,m,n)+=P(i,j)*
qa(t-1,j,k,l,m,n,p);
            }
        }
    }
}

    }
}
for (i=0;i<=1;i++) {
    for (j=0;j<=1;j++) {
        for (k=0;k<=1;k++) {
            for (l=0;l<=1;l++) {
                for (m=0;m<=1;m++) { // !!5
                    for (n=0;n<=1;n++) qa(t,i,j,k,l,m,n)=qb(t,i,j,k,l,m,n)*
prob(t,i,j,k,l,m,n);
                }
            }
        }
    }
}

    }
}
qbefore(t,0)=sum(qb(t,0));
qbefore(t,1)=sum(qb(t,1));
qafter(t,0)=sum(qa(t,0));
qafter(t,1)=sum(qa(t,1));
dvariable sumqa=sum(qaafter(t));
qa(t)/=sumqa;
qafter(t,0)/=sumqa;
qafter(t,1)/=sumqa;
ff1=-log(1.e-50+sumqa);
}
ff+=ff1;
ff+=.1*norm2(f);
REPORT_SECTION
dvar_matrix out(1,2,op1,nperiods);
out(1)=trans(qbefore)(1);
out(2)=trans(qaafter)(1);
{
    ofstream ofs("qbefore4.tex");
    for (int t=5;t<=nperiods;t++)
    {
        ofs << (t-4)/100. << " " << qbefore(t,0) << endl;
    }
}
{
    ofstream ofs("qafter4.tex");
    for (int t=5;t<=nperiods;t++)
    {
        ofs << (t-4)/100. << " " << qaafter(t,0) << endl;
    }
}
}

```

```

    report << "#qbefore    qafter" << endl;
    report << setfixed << setprecision(3) << setw(7) << trans(out) << endl;
RUNTIME_SECTION
    maximum_function_evaluations 20000
    convergence_criteria 1.e-6
TOP_OF_MAIN_SECTION
    arrmblsize=500000;
    gradient_structure::set_GRADSTACK_BUFFER_SIZE(400000);
    gradient_structure::set_CMPDIF_BUFFER_SIZE(2100000);
    gradient_structure::set_MAX_NVAR_OFFSET(500);
GLOBALS_SECTION
    #include <fvar.hpp>
    // !!5
    dvariable phi(const dvariable& a1,const dvariable& a2,const dvariable& a3,
        const dvariable& a4,const dvariable& a5,const dvar_vector& f)
    {
        return  a1*f(1)+a2*f(2)+a3*f(3)+a4*f(4)+a5*f(5);
    }

```



## Chapter 5

# Econometric Models – simultaneous equations

### Simultaneous Equations Models

For each  $t$ ,  $1 \leq t \leq T$  let  $y_t$  be an  $n$  dimensional vector and  $x_t$  be an  $n$  dimensional vector. Let  $B$  and  $\Gamma$  be  $(n \times n)$  and  $(n \times m)$  matrices and suppose that the relationship

$$By_t + \Gamma x_t = u_t$$

holds where the  $u_t$  are  $n$  dimensional random vectors of disturbances. The  $y_t$  are the endogenous variables in the system. The  $x_t$  are predetermined variables in the sense that they are independent of  $u_t$ . Note that for autoregressive models the  $x_t$  may contain values of  $y_j$  for  $j < i$ . In general not all of the coefficients of  $B$  and  $\Gamma$  are estimable. Interesting cases have special structure which are determined by the particular parameterization of  $B$ ,  $\Gamma$  and  $D$ . In particular it is generally assumed that  $B_{ii} = 1$  for  $1 \leq i \leq n$  and that  $B^{-1}$  exists.

### Full Information Maximum Likelihood (FIML)

Assume that for each  $t$ ,  $u_t$  has a multivariate normal distribution with mean 0 and covariance matrix  $D$ . The log-likelihood function for  $B, \Gamma$ , and  $D$  is given by

$$L(B, \Gamma, D) = T/2 \log(|B|^2) - T/2 \log(|D|) - 1/2 \sum_{t=1}^T [By_t + \Gamma x_t]' D^{-1} [By_t + \Gamma x_t] \quad (5.1)$$

### Concentrating out $D$ for the FIML

If there are no constraints on  $D$  the value of  $D$  which maximizes 5.1 can be solved for in terms of the other parameters and observations. This value  $\hat{D}$  is given by

$$\hat{D} = 1/T \sum_{t=1}^T [By_t + \Gamma x_t]' [By_t + \Gamma x_t] \quad (5.2)$$

substituting this value into (0.1) it can be shown that

$$1/2 \sum_{t=1}^T [By_t + \Gamma x_t]' \hat{D}^{-1} [By_t + \Gamma x_t]$$

is a constant which can be ignored for the maximization so that equation 5.2

$$\tilde{L}(B, \Gamma) = T/2 \log(|B|^2) - T/2 \log(|\hat{D}|) \quad (5.3)$$

and the FIML estimates for  $B$  and  $\Gamma$  can be found by maximizing  $\tilde{L}(B, \Gamma)$ .

When there are constraints on the parameters of  $D$  then  $\tilde{D}$  is no longer the maximum likelihood estimate for  $D$  so it is necessary to maximize 5.1 which is in general a numerically unstable problem. To successfully carry out the optimization it is necessary to obtain reasonable initial estimates for the parameters of  $B$  and  $\Gamma$  and to use a good method for parameterizing  $D$ . Initial estimates for  $B$  and  $\Gamma$  can be obtained from ordinary least squares (OLS), that is find the values of  $B$  and  $\Gamma$  which minimize

$$\sum_{t=1}^T \|y_t - B^{-1}\Gamma x_t\|^2$$

To parameterize  $D$  note that  $\hat{D}$  is an estimate of  $D$  so that we can parameterize  $D$  by

$$D = A\hat{D}A'$$

where  $A$  is a lower triangular matrix. If  $U$  is the choleski decomposition of  $D$  and  $\hat{U}$  is the choleski decomposition of  $\hat{D}$  then  $A = \hat{U}^{-1}U$ . It follows that  $A$  should be close to the identity matrix which is a good initial estimate for  $A$ .

## Evaluating the model's performance

To evaluate the model's performance simulated data were generated. The form of the model is

$$\begin{aligned} y_{t1} + y_{t4} + y_{t5} - 2 + 0.45y_{t-1,1} &= u_{t1} \\ 0.1y_{t1} + y_{t2} + 2.0y_{t5} - 1 - 0.6y_{t-1,1} + 0.25y_{t-1,2} &= u_{t2} \\ 0.3y_{t1} - 0.2y_{t2} + y_{t3} + 1 &= u_{t3} \\ 1.4y_{t2} - 3.1y_{t3} + y_{t4} + 1 &= u_{t4} \end{aligned}$$

$$y_{t3} + y_{t4} + y_{t5} = u_{t5} \quad (5.4)$$

with a covariance matrix

$$D = \begin{pmatrix} 0.512 & 0.32 & 0.256 & -1.28 & 0 \\ 0.32 & 0.328 & -0.16 & -0.8 & 0 \\ 0.256 & -0.16 & 1.728 & 0.16 & 0.8 \\ -1.28 & -0.8 & 0.16 & 4.8 & 0.8 \\ 0 & 0 & 0.8 & 0.8 & 0.928 \end{pmatrix}$$

$$B = \begin{pmatrix} 1 & 0 & 0 & 1 & 1 \\ 0.1 & 1 & 0 & 0 & 2 \\ 0.3 & -0.2 & 1 & 0 & 0 \\ 0 & 1.4 & -3.1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 1 \end{pmatrix}$$

$$\Gamma = \begin{pmatrix} -2 & 0.45 & 0 \\ -1 & -0.6 & 0.25 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

For this model  $n = 5$ ,  $m = 3$ , and  $x_t = (1, y_{t-1,1}, y_{t-1,2})$ .

The eigenvalues of  $D$  are (0.006610.135830.49622.211625.44573) Having a small eigenvalue tends to produce simulated data that are difficult to analyze.

Forty time periods of data were generated by the simulator. The simulated  $y$  values are:

```

1.63252 3.00223 1.70246 1.34813 -1.12202
-2.87857 -7.72402 -3.88482 -1.24196 4.71024
1.12975 -7.92719 -3.85188 -2.33007 4.2984
1.48112 -2.25692 -1.15585 -2.26166 3.01061
-2.91887 -5.65015 -2.74198 -0.695815 4.51346
2.29715 0.524946 0.0268777 1.07624 -0.0898846
1.32854 6.17993 2.51613 1.67248 -2.39914
0.5661 -2.53219 -0.966376 0.00820516 1.76543
0.353591 -3.81146 -2.04431 -1.48574 2.67208
-2.22887 -2.33436 -1.66284 0.646399 2.26448
2.29896 -6.42238 -2.41106 -1.70633 3.50028
0.145878 1.85161 0.646578 -0.380955 0.709761
-0.779376 -7.60611 -3.79636 -1.63017 4.02658
-0.107371 -5.61361 -2.35816 -1.77719 3.67762
0.662221 -5.78832 -2.19632 -2.03071 4.37961
-0.570661 -7.42505 -3.28544 -2.94125 5.19422
0.0953742 -1.80617 -1.06915 -0.0320784 2.00018
-0.406986 -4.96143 -2.8084 -0.948902 3.1811
1.07219 -7.92608 -2.95484 -3.17022 5.12702
-0.495144 1.33611 -0.357291 -0.0260083 0.360653
-0.637878 -8.76117 -3.81638 -1.77116 4.82796
1.59717 -3.18571 -1.72708 -1.93975 2.79462

```

```

-1.13013 -2.20942 -1.30198 -0.603895 2.29486
-1.0103 -7.90106 -3.65303 -1.07367 4.66283
-1.02985 -3.00268 -1.63388 0.309992 2.97876
0.176882 -7.96282 -3.60299 -1.86289 4.86943
1.16904 -1.07952 -0.0969977 -0.74563 2.38399
-0.636119 -2.84841 -1.43676 -0.38474 2.51142
-1.72929 -5.39866 -2.51289 0.0978131 3.786
3.56302 3.79343 2.05613 1.43836 -1.2029
0.15806 -0.863882 -0.302119 -1.19212 1.38518
1.37323 -1.94413 -0.537631 -0.751294 1.42083
-0.404075 -8.53817 -3.58618 -3.33976 5.69071
0.362091 -5.78568 -2.46635 -2.33359 4.21899
-2.26158 -12.7075 -6.07426 -3.62455 8.49292
1.20438 -5.44629 -2.30249 -2.02905 3.82742
1.41463 -1.71734 -0.788698 -1.90306 2.2595
0.897156 1.28039 0.693579 0.318737 0.385857
-0.0330384 -1.55642 -0.189474 0.312385 1.57168
1.5747 0.827181 1.26032 0.813312 0.270432

```

For the  $x$  values the first time periods data  $x_0 = (1, 1, 2)$  were supplied. The simulated  $x$  values are:

```

1 1 2
1 1.63252 3.00223
1 -2.87857 -7.72402
1 1.12975 -7.92719
1 1.48112 -2.25692
1 -2.91887 -5.65015
1 2.29715 0.524946
1 1.32854 6.17993
1 0.5661 -2.53219
1 0.353591 -3.81146
1 -2.22887 -2.33436
1 2.29896 -6.42238
1 0.145878 1.85161
1 -0.779376 -7.60611
1 -0.107371 -5.61361
1 0.662221 -5.78832
1 -0.570661 -7.42505
1 0.0953742 -1.80617
1 -0.406986 -4.96143
1 1.07219 -7.92608
1 -0.495144 1.33611
1 -0.637878 -8.76117
1 1.59717 -3.18571
1 -1.13013 -2.20942
1 -1.0103 -7.90106
1 -1.02985 -3.00268
1 0.176882 -7.96282
1 1.16904 -1.07952
1 -0.636119 -2.84841
1 -1.72929 -5.39866
1 3.56302 3.79343
1 0.15806 -0.863882
1 1.37323 -1.94413
1 -0.404075 -8.53817
1 0.362091 -5.78568
1 -2.26158 -12.7075

```

1 1.20438 -5.44629  
 1 1.41463 -1.71734  
 1 0.897156 1.28039  
 1 -0.0330384 -1.55642

## Results of (FIML) for unconstrained $D$

For the estimation process all the elements of the matrices  $B$  and  $\Gamma$  with value 0 were fixed at their correct value. The FIML estimates for unconstrained covariance matrix  $D$  are given below.

$$B = \begin{pmatrix} 1 & 0 & 0 & 0.364395 & 0.364395 \\ 0.238411 & 1 & 0 & 0 & 1.37593 \\ 0.042875 & -0.330484 & 1 & 0 & 0 \\ 0 & 1.93026 & -4.90367 & 1 & 0 \\ 0 & 0 & 1.06339 & 1.09851 & 1 \end{pmatrix}$$

$$\Gamma = \begin{pmatrix} -0.917978 & 0.431377 & 0 \\ 0.473915 & -0.491422 & 0.19981 \\ 0.441089 & 0 & 0 \\ -0.126701 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

$$D = \begin{pmatrix} 0.938236 & 0.843743 & 0.506127 & -1.38383 & 0.314262 \\ 0.843743 & 1.55844 & 0.732235 & -0.591771 & 1.37195 \\ 0.506127 & 0.732235 & 0.430091 & -0.805866 & 0.62244 \\ -1.38383 & -0.591771 & -0.805866 & 4.18591 & -0.0363513 \\ 0.314262 & 1.37195 & 0.62244 & -0.0363513 & 1.75939 \end{pmatrix}$$

## Results of (FIML) for constrained $D$

Since  $D_{51} = 0$ , and  $D_{52} = 0$ , these values were not well estimated by the unconstrained FIML procedure. Suppose that we know that their values should be 0 and that the value of  $D_{55} \leq 1.0$ . We incorporate this knowledge into the model by using penalty functions.

$$B = \begin{pmatrix} 1 & 0 & 0 & 0.594218 & 0.594218 \\ -0.321482 & 1 & 0 & 0 & 1.97809 \\ 0.0416175 & -0.365572 & 1 & 0 & 0 \\ 0 & 2.48468 & -6.10763 & 1 & 0 \\ 0 & 0 & 0.968057 & 1.02738 & 1 \end{pmatrix}$$

$$\Gamma = \begin{pmatrix} r - 1.3418 & 0.448342 & 0 \\ -1.14717 & -0.593754 & 0.183788 \\ 0.372114 & 0 & 0 \\ -0.0640792 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

$$D = \begin{pmatrix} 0.593424 & -0.325467 & 0.298836 & -1.43231 & 0.00401209 \\ -0.325467 & 0.650371 & -0.234747 & 0.441841 & 4.48456e - 06 \\ 0.298836 & -0.234747 & 0.258147 & -0.900105 & 0.255262 \\ -1.43231 & 0.441841 & -0.900105 & 6.13619 & 0.180376 \\ 0.00401209 & 4.48456e - 06 & 0.255262 & 0.180376 & 1.00262 \end{pmatrix}$$

## Code for (FIML) for constrained $D$

This is the code in the TPL file split up by sections and commented on. The `DATA_SECTION` defines the data and some size aspects of the model structure. Objects which are prefixed by `init_` will be read in from the data file.

```
// This version incorporates constraints via penalty functions.
//This is sample code to determine the parameters of a
//sim,ultaneous equations model. The notation follows
//that of Hamilton, Times Series Analysis, chapter 9.
//the general form of the model is
//
//   By_t + Gamma x_t =u_t
//
//for t=1,...,T. The u_t have covariance matrix D.

DATA_SECTION
init_int T // the number of observations
init_int dimy // dimension of the vector of
// endogenousvariables
init_int dimx // dimension of the vector of
// predetermined variables
init_int num_Bpar // the number of parameters in
// the elements of B to be estimated
init_int num_Gpar // the number of parameters in
// the elements of Gamma to be estimated
init_matrix y(1,T,1,dimy) // the y_t
init_matrix x(1,T,1,dimx) // the x_t
int dimy1
!! dimy1=dimy*(dimy+1)/2; // size of symmetric matrix
```

The `PARAMETER_SECTION` describes the model's parameters. Objects which are prefixed by `init_` are the independent variables of the model. For example `Bpar` is used to parameterize the nonzero elements of `B`. `ch_Dpar` is used to parameterize the lower triangular matrix of the correction from `emp_D` to the covariance matrix `D`. The minimization is done in a number of phases. The parameter `kx` is used to have a parameter which becomes active in phase 4,

so that the minimization will take place in four stages. This parameter does not enter into the “real” part of the model.

```

PARAMETER_SECTION
  init_vector Bpar(1,num_Bpar)
  init_vector Gpar(1,num_Gpar)
  init_vector ch_Dpar(1,dimy1,2)
  matrix B(1,dimy,1,dimy)
  matrix D(1,dimy,1,dimy) // the covariance matrix for the
                          // disturbances u_t
  matrix emp_D(1,dimy,1,dimy) // the covariance matrix for the
  matrix Gamma(1,dimy,1,dimx)
  matrix ch_D(1,dimy,1,dimy)
  matrix z(1,T,1,dimy);
  objective_function_value f
  init_number kx(4);

```

The PROCEDURE\_SECTION is where the models calculations are carried out. It is split up into a set of functions where the model specific pieces of code (different code for different models) are located. Finally the optimization for parameter estimation is calculated. This depends on the phase of the optimization procedure. A `switch` statement is used to vary the form of the objective function depending on the phase. The function `current_phase()` return the number of the current phase of the optimization. The function `last_phase()` returns 1 (“true”) if the current phase is the last phase of the optimization. Quadratic penalty functions are put on the model’s parameters and the penalty weights are decreased in subsequent phase. this procedure help to stabilize the optimization when several model parametes are highly correlated.

```

PROCEDURE_SECTION
  fill_B(); // this will vary from model to model
  fill_Gamma(); // this will vary from model to model

  calculate_empirical_copvariance_matrix();

  fill_D(); // this will vary from model to model

  calculate_constraints(); // this will vary from model to model

  int sgn;
  switch (current_phase())
  {
  case 1:
    {
      f+=0.1*norm2(Bpar);
      f+=0.1*norm2(Gpar);
      f+=0.1*norm2(ch_Dpar);
      dvar_matrix Binv=inv(B);
      for (int t=1;t<=T;t++)
      {
        dvar_vector z=y(t)+Binv*Gamma*x(t);
        f+=z*z;
      }
      break;
    }
  default:

```

```

{
  f+= -0.5*T*log(square(det(B)))
    +0.5*T*ln_det(D,sgn);

  dvar_matrix Dinv=inv(D);
  dvariable f1=0.0;
  for (int t=1;t<=T;t++)
  {
    dvar_vector z=B*y(t)+Gamma*x(t);
    f1+=z*(Dinv*z);
  }
  f+=0.5*f1;
  if (!last_phase())
  {
    f+=0.1*norm2(Bpar);
    f+=0.1*norm2(Gpar);
    f+=0.1*norm2(ch_Dpar);
  }
  else
  {
    f+=0.001*norm2(Bpar);
    f+=0.001*norm2(Gpar);
    f+=0.001*norm2(ch_Dpar);
  }
}
}

f+=square(kx);

FUNCTION fill_B
  B.initialize();
  for (int i=1;i<=dimy;i++)
    B(i,i)=1.0;

  // this is part of the special structure of the model
  int ii=1;
  B(2,1)=Bpar(1);
  B(3,1)=Bpar(2);

  B(3,2)=Bpar(3);
  B(4,2)=Bpar(4);

  B(4,3)=Bpar(5);
  B(5,3)=Bpar(6);

  B(5,4)=Bpar(7);
  B(1,4)=Bpar(8);

  B(1,5)=Bpar(8);
  B(2,5)=Bpar(9);

FUNCTION fill_Gamma
  Gamma.initialize();

  // this is the part of special structure of the model
  Gamma(1,1)=Gpar(1);
  Gamma(2,1)=Gpar(2);

```



```

Gamma(3,1)=Gpar(3);
Gamma(4,1)=Gpar(4);

Gamma(1,2)=Gpar(5);
Gamma(2,2)=Gpar(6);

Gamma(2,3)=Gpar(7);

FUNCTION fill_D

  ch_D.initialize();
  // this is the special structure of the model
  int ii=1;
  for (int i=1;i<=dimy;i++)
  {
    for (int j=1;j<=i;j++)
      ch_D(i,j)=ch_Dpar(ii++);
    ch_D(i,i)+=1;
  }

  D=ch_D*emp_D*trans(ch_D); // so Ch_D is the Cholesky
                          // decomposition of D
FUNCTION calculate_empirical_copvariance_matrix

  for (int t=1;t<=T;t++)
    z(t)=B*y(t)+Gamma*x(t);

  emp_D=empirical_covariance(z);

FUNCTION calculate_constraints

  double wt=1.0;
  switch (current_phase())
  {
  case 1:
    wt=1.0;
    break;
  case 2:
    wt=10.0;
    break;
  case 3:
    wt=100.0;
    break;
  default:
    wt=1000.0;
    break;
  }
  if (D(5,5)>1.0)
    f+=wt*square(D(5,5)-1.00);

  f+=wt*square(D(5,1));
  f+=wt*square(D(5,2));

```

The REPORT\_SECTION prints out a report of the imodel's results.

```

REPORT_SECTION
  report << "B" << endl;

```

```
report << B << endl;
report << "Gamma" << endl;
report << Gamma << endl;
report << "D" << endl;
report << D << endl;
report << "eigenvalues of D" << endl;
report << eigenvalues(D) << endl;
report << "y" << endl;
report << y << endl;
report << "x" << endl;
report << x << endl;
```

## Chapter 6

# Multivariate GARCH

The Vector Autoregressive Moving Average Garch process combines the Vector Autoregressive Moving Average (VARMA) processes with the Vector Garch (generalized autoregressive conditional heteroscedastic) processes.

### Formulation of the VARMA GARCH process

The VARMA GARCH process of type  $(p, q, r, s)$  is given by a series  $Y_t$  for  $t = -p + 1, \dots, n$  where for each value of  $t$ ,  $Y_t$  is an  $m$  dimensional vector. For  $t > 0$  the  $Y_t$  are assumed to satisfy a relationship of the form

$$Y_t = \mu + \sum_{l=1}^p A_l(Y_{t-l} - \mu) + \sum_{l=0}^q B_l \epsilon_{t-l} \quad (6.1)$$

where the  $\mu$  is an  $m$  dimensional vector,  $A_l$  and  $B_l$  are  $m \times m$  matrices,  $B_0$  is the identity matrix, and the  $\epsilon_t$  are multivariate (normal) random vectors with means 0, covariance matrices  $\Sigma_t$ , and  $E(\epsilon_t \epsilon_{t'}) = 0$  if  $t \neq t'$ . Let

$$r_t = Y_t - \mu - \sum_{l=1}^p A_l(Y_{t-l} - \mu) \quad (6.2)$$

be the vector of model residuals or “shocks”<sup>1</sup> These residuals are assumed to contribute to the covariance matrix in the next time period. The  $\Sigma_t$  evolve according to one of several relationships. The DVEC relationship:

$$\Sigma_t = \Omega + \sum_{l=1}^r F_l \otimes r_{t-l} r'_{t-l} + \sum_{l=1}^s G_l \otimes \Sigma_{t-l} \quad (6.3)$$

In equation 6.3 the matrices  $F_l$  and  $G_l$  are symmetric and the operator  $\otimes$  denotes the element-wise product of matrices. This parameterization does not restrict the resulting

---

<sup>1</sup>For the moving average model ( $q > 0$ ) one might argue that since the previous values of  $r_t$  have been observed the shock part of  $r_t$  say  $d_t$  is given by  $d_t = r_t - \sum_{l=1}^q B_l r_{t-l}$  but this has not been done at present.

matrix to be positive definite so that some care is necessary to ensure the stability of the resulting model. The BEKK relationship:

$$\Sigma_t = \Omega + \sum_{l=1}^r F_l r_{t-l} r'_{t-l} F'_l + \sum_{l=1}^s G_l \Sigma_{t-l} G'_l \quad (6.4)$$

The basic DVEC and BEKK parameterization can be extended by modifying components of the  $r_t$  to reflect the asymmetric response to positive and negative values.

$$\begin{aligned} \eta_{ij} &= \epsilon_{ij} / \alpha_j & \text{if } \epsilon_{ij} \geq 0 \\ \eta_{ij} &= \epsilon_{ij} \alpha_j & \text{if } \epsilon_{ij} < 0 \end{aligned} \quad (6.5)$$

This modified form will be referred to as the DVECI and BEKKAI parameterizations.

$$\Sigma_t = \Omega + \sum_{l=1}^r F_t \otimes \eta_{t-l} \eta'_{t-l} + \sum_{l=1}^s G_l \otimes \Sigma_{t-l} \quad (6.6)$$

$$\Sigma_t = \Omega + \sum_{l=1}^r F_l \eta_{t-l} \eta'_{t-l} F'_l + \sum_{l=1}^s G_l \Sigma_{t-l} G'_l \quad (6.7)$$

## Setting a value for $\Sigma_1$

The value for the parameters in  $\Sigma_1$  are often poorly determined and simply letting them be free parameters can lead to instability and initial transient effects in the model. To stabilize the parameterization we have calculated  $\Sigma_1$  through  $\Sigma_{\max\{r,s\}}$  from the condition

$$\widehat{\Omega} = \Sigma + \sum_{l=1}^q B_l \Sigma B'_l \quad (6.8)$$

where

$$\widehat{\Omega} = \frac{1}{n} \sum_{t=1}^n \hat{\epsilon}_t \hat{\epsilon}'_t \quad (6.9)$$

denotes the empirical covariance matrix formed from the models residuals

$$\hat{\epsilon}_t = Y_t - \mu - \sum_{l=1}^p A_l (Y_{t-l} - \mu). \quad (6.10)$$

## Ensuring that the $\Sigma_t$ are positive definite

The DVEC parameterization can produce matrices which are not positive definite and the BEKK parameterization can produce matrices which are almost not positive definite (much as a positive number can get arbitrarily close to 0). At worst this will lead to a failure in the model to converge and at best it makes the estimation somewhat unstable. To improve model performance the BEKK and DVEC operations are followed by a modification of the resulting  $\Sigma_t$  which makes them more positive definite. The first problem is to get a notion

of what is meant by small for a particular problem. This is accomplished by first scaling the  $\Sigma_t$  to produce a matrix  $\Lambda_t$  where

$$\Lambda_{ij} = \Sigma_{t_{ij}} / \sqrt{\Sigma_{t_{ij}} \Sigma_{t_{ij}}} \quad (6.11)$$

The terms  $\Lambda_{ii}$  are then bounded above 1.e-3 ie they are replaced in a differentiable fashion with numbers that are /ge 1.e-3. using the `posfun` function. In addition the correlation matrix  $\Lambda_{ij} / \sqrt{\Lambda_{t_{ij}} \Lambda_{t_{ij}}}$  is decomposed via a choleski decomposition, the divisors of which is forced to be  $gt > 0.3$  in a differentiable fashion using the `posfun` function. .

the above operations leave a matrix which is sufficiently positive definite and close enough to  $\Sigma_{t_1}$  unchanged.

## Missing data

Missing data points are included into the model as parameters to be estimated. If there are a substantial number of missing data points this will induce bias into the estimates.

## The likelihood function

The model was fit by maximum-likelihood or more correctly by finding the mode of the Bayesian posterior distribution. A robust likelihood function which is a mixture of a normal distribution and a Cauchy distribution is employed. The amount of robustness can be changed by the user.

## Model Selection

Model selection consists of fitting the model to the data for various values of the parameters  $(p, q, r, s)$  and trying to determine the simplest model which adequately fits the data, if any.

The two criteria which are used for this are the likelihood ratio test and investigation of the residuals in the form of the Box-Ljung statistic. The likelihood-ratio test is used for general model selection, while The Box-Ljung statistic is used to investigate whether the model can adequately fit the changes in the covariance matrices  $\Sigma_t$  which occur over time.

## The Box-Ljung statistic

The following Box-Ljung Statistic was employed to test the ability of the model to model the time varying covariance structure of the time series. This statistic is calculated from the estimated standardized residuals  $z_t$  for  $t = 1, \dots, n$  where for each  $t$   $z_t$  is an  $m$  dimensional vector. The  $z_i$  are obtained in the calculations necessary to calculate the log-likelihood function.

$$\begin{aligned}
 \hat{\mu}_j &= \frac{1}{n} \sum_{i=1}^n z_{ij} \\
 z'_{ij} &= z_{ij} - \hat{\mu}_j \\
 \hat{\sigma}_{jk} &= \frac{1}{n} \sum_{i=1}^n z'_{ij} z'_{ik} \\
 \gamma_{ijk} &= \frac{\frac{1}{n-l} \sum_{i=1}^{n-l} (z'_{ij} z'_{ik} - \hat{\sigma}_{jk})(z'_{i,j+l} z'_{i,k+l} - \hat{\sigma}_{jk})}{\frac{1}{n} \sum_{i=1}^n (z'_{ij} z'_{ik} - \hat{\sigma}_{jk})^2}
 \end{aligned} \tag{6.12}$$

Under the null hypothesis that the model is adequate and if the  $z_i$  are normally distributed then the sum

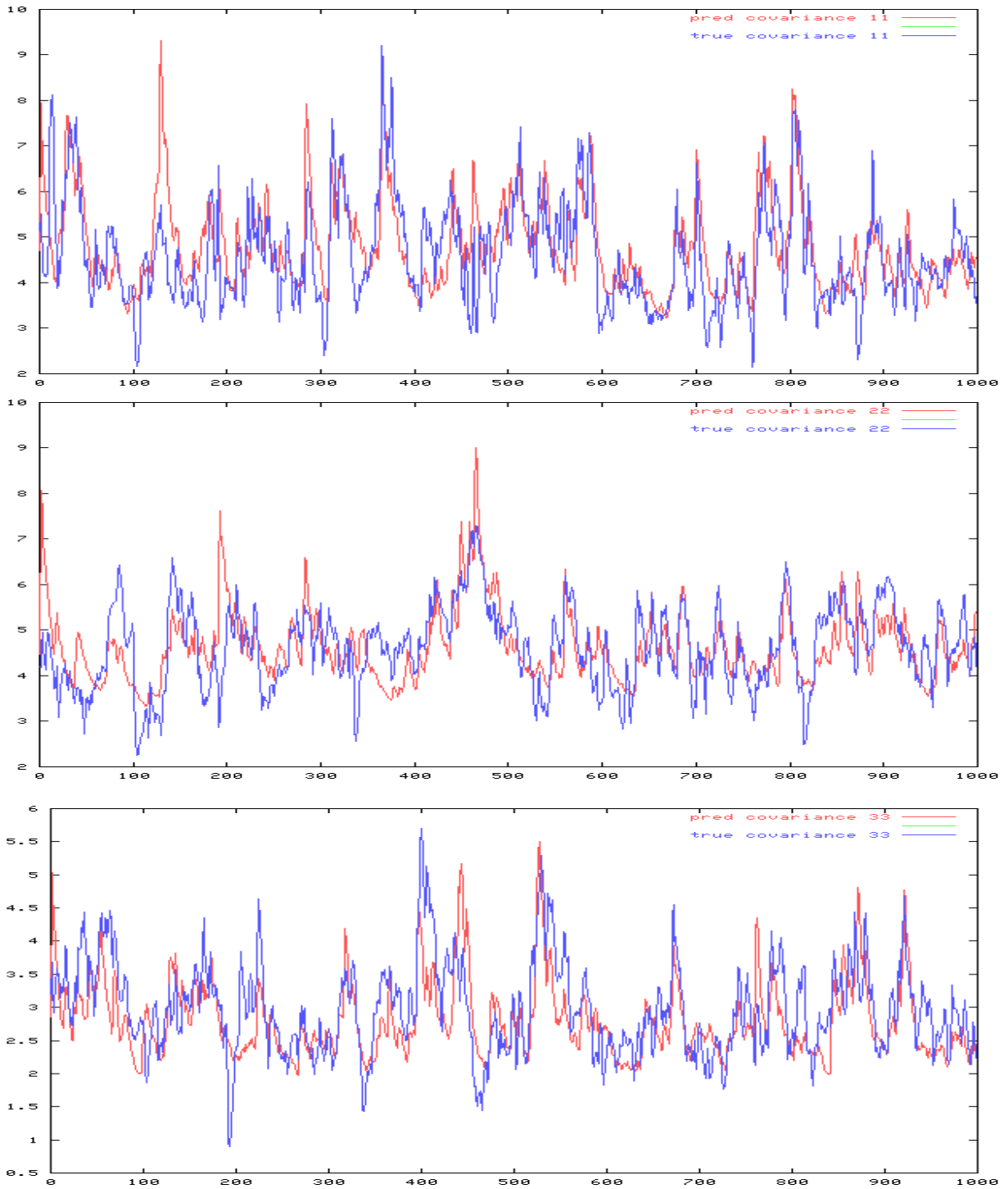
$$LB(K)_{ij} = n \sum_{k=1}^k w_k \gamma_{ijk}^2$$

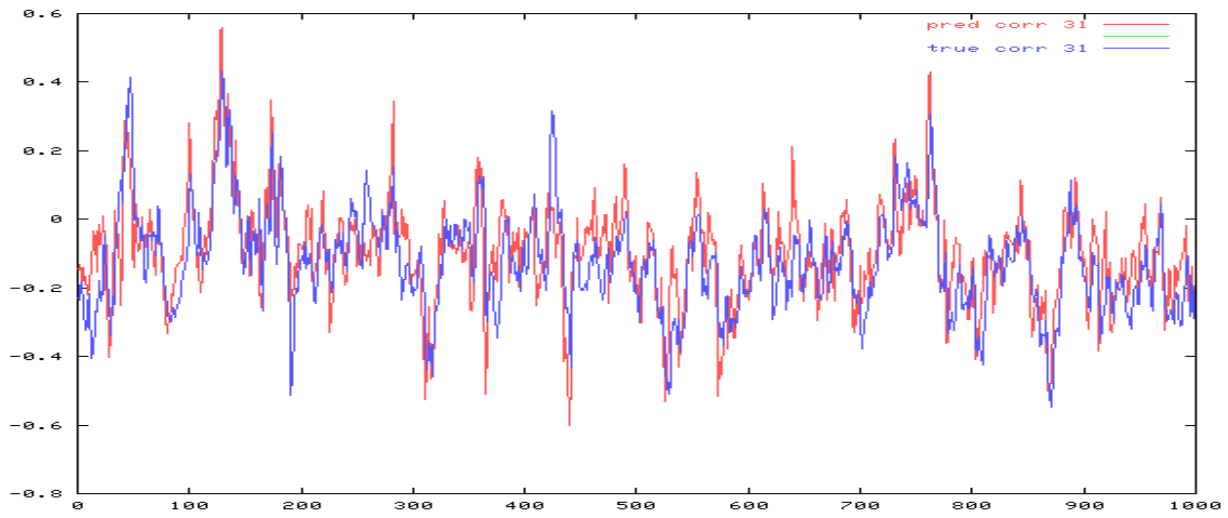
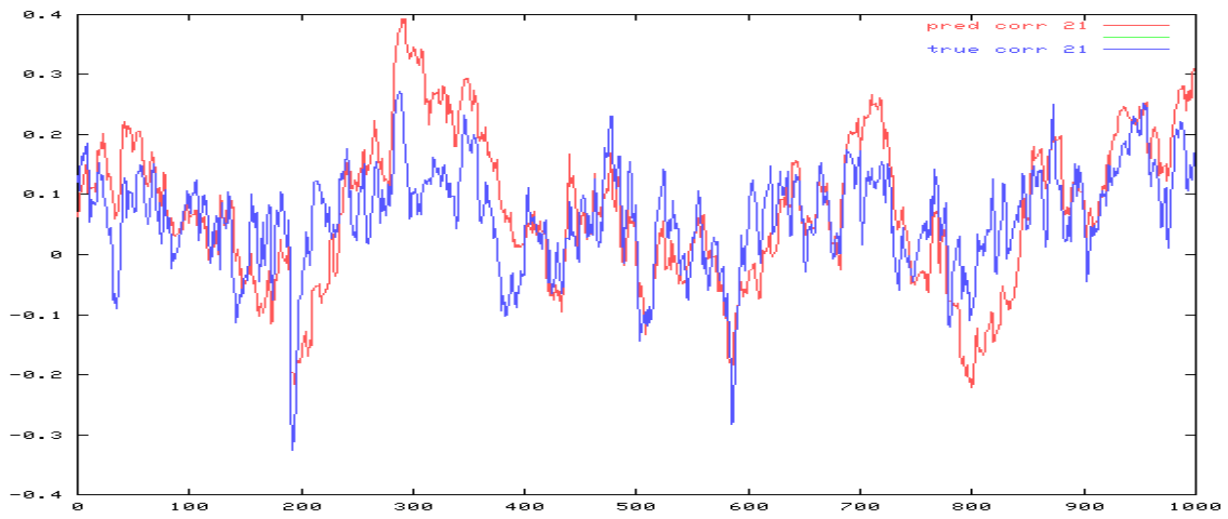
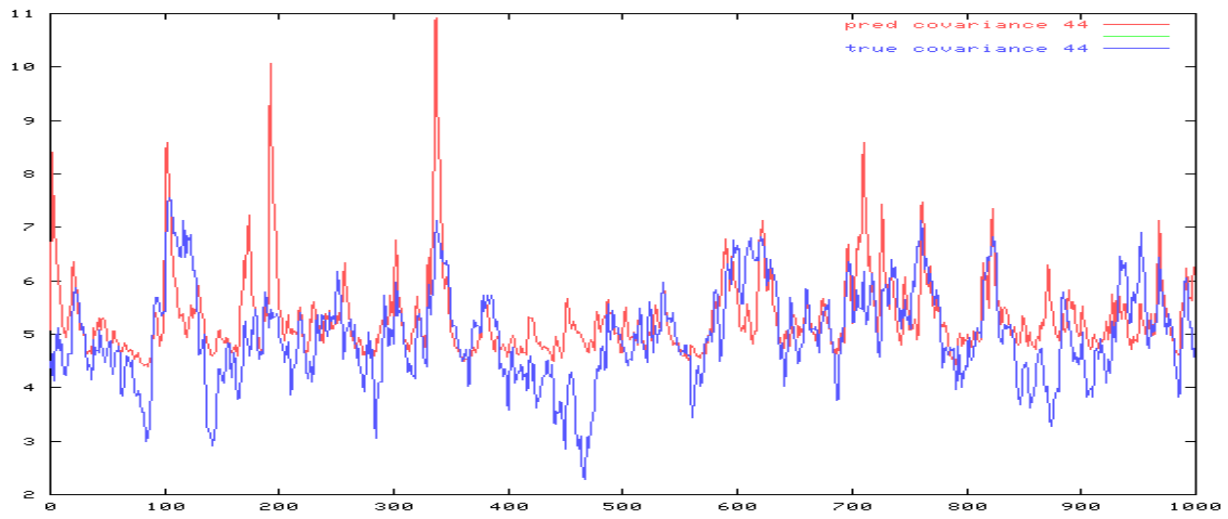
is asymptotically distributed as a  $\chi^2$  random variable with  $K$  degrees of freedom. Here  $w_k = (n + 2)/(n - k)$ .

## Analysis of Simulated data

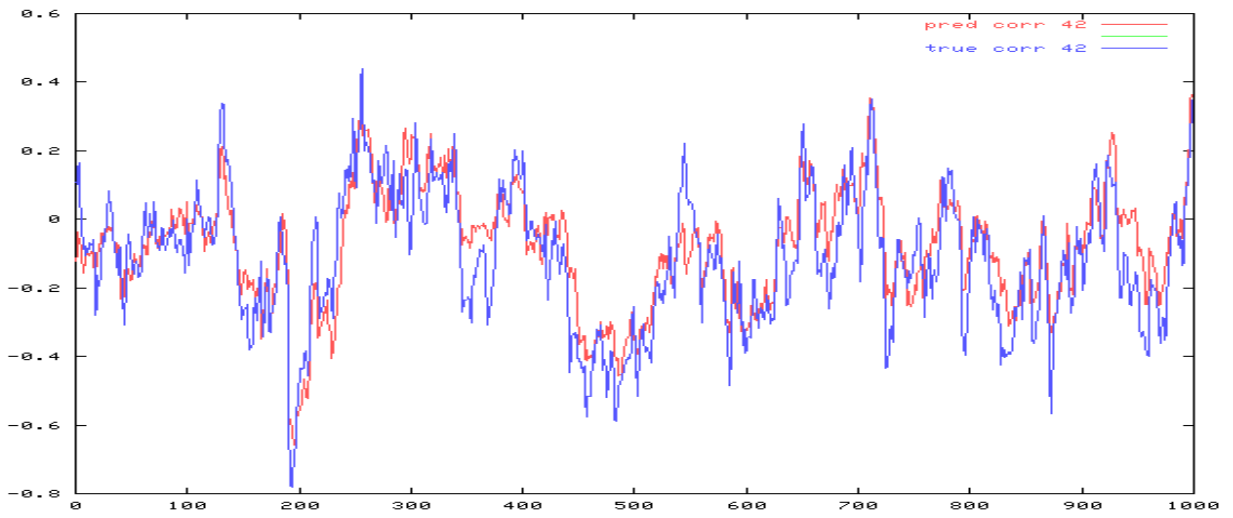
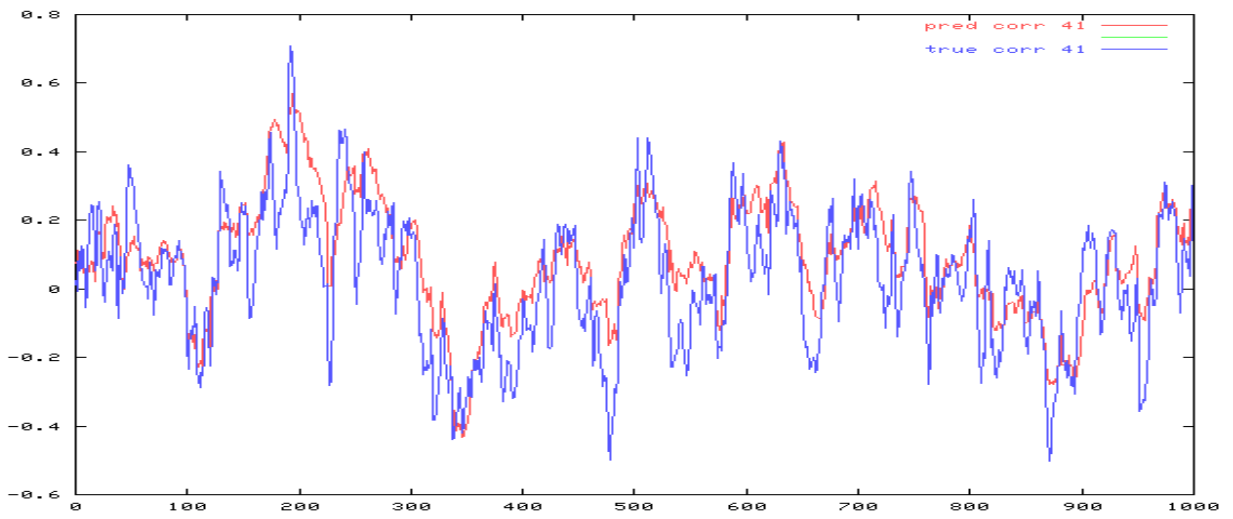
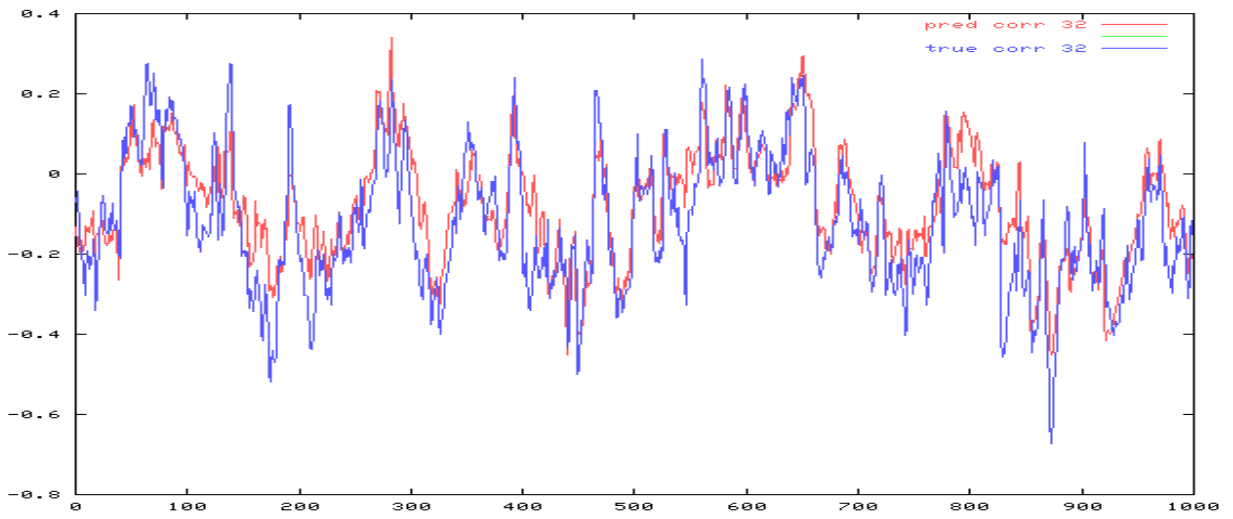
One method to get an idea how well a statistical model works is to use it with simulated data where the true values of the parameters being estimated are known. A simple simulator which can generate data sets is included with the mgarch package. The simulator generated a four dimensional set of 1,000 observations. A type 1,1,1,1 process was simulated and analyzed.

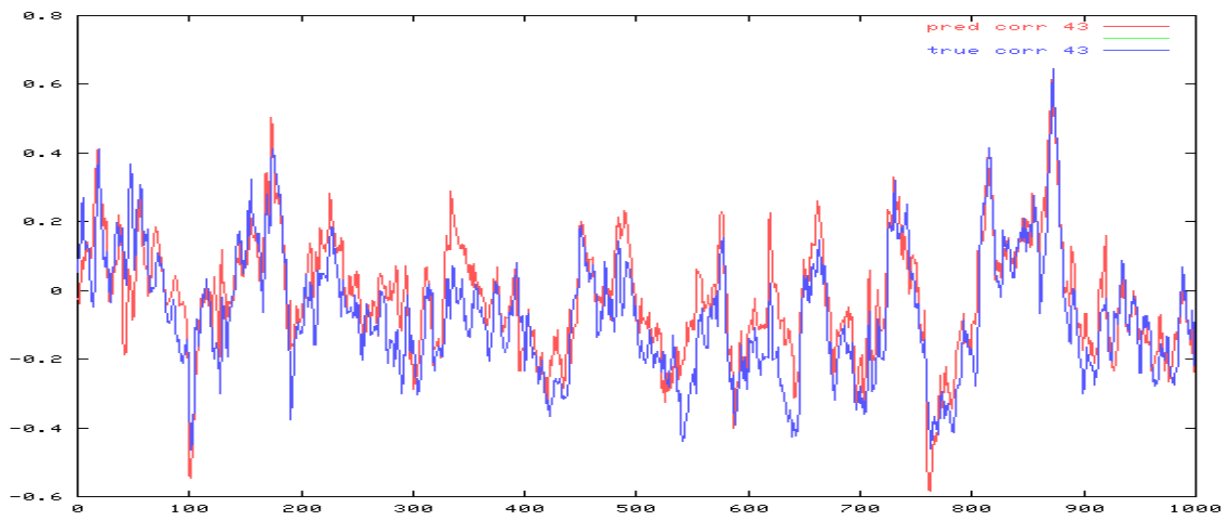
The following plots show the actual and predicted values for the diagonal variance and correlation terms for the analysis with a type 1,1,1,1 model.











## Analysis of Real Data

The data consist of daily observations of the German Mark-US Dollar and Japanese Yen-US dollar exchange rates as well as the SP-500 and Tokyo (TOKYOSE) stock exchange indices. For this data set  $m = 4$  and there were 1301 time periods with 211 missing values.

Model Parameters log-likelihood directory

p,q,r,s

VARMA

0,0,0,0 221 -1382.56 000

1,0,0,0 241 -1322.47 100

1,1,0,0 253 -1308.57 110

VARMA with DVEC

0,0,1,1 241 -1050.87

1,1,2,1 283 -928.518

1,2,1,1 289 -924.755

VARMA with DVECI

1,1,2,1a 287 -887.764

1,2,1,1a 293 -888.531

Ljung-Box statistic ( $\chi^2$  with 10 degrees of freedom)

VARMA

0,0,0,0      138.953 52.902 26.351 19.171  
52.902 222.502 154.708 59.681  
26.351 154.708 60.328 87.031  
19.171 59.681 87.031 68.889

1,1,0,0      154.977 74.511 19.329 11.472  
74.511 177.016 130.295 59.084  
19.329 130.295 47.499 72.724  
11.472 59.084 72.724 49.329

VARMA with DVEC

0,0,1,1      3.728 13.180 17.682 17.633  
13.180 11.496 25.846 6.016  
17.682 25.846 7.610 6.791  
17.633 6.016 6.791 13.398

1,1,1,1      4.239 9.519 10.866 10.885  
9.519 6.434 21.734 8.047  
10.866 21.734 4.089 8.318  
10.885 8.047 8.318 12.814

1,2,1,1      5.660 10.348 11.029 11.557  
10.348 7.011 21.727 7.039  
11.029 21.727 4.819 7.908  
11.557 7.039 7.908 10.684

1,1,2,1      6.920 11.698 11.464 12.593  
11.698 4.914 24.677 8.179  
11.464 24.677 2.399 8.855  
12.593 8.179 8.855 10.985

VARMA with DVECI

1,2,1,1a      4.352 9.658 9.402 8.542  
9.658 7.646 17.516 8.416  
9.402 17.516 5.795 7.108  
8.542 8.416 7.108 10.483

1,1,2,1a      4.785 17.077 8.760 10.487

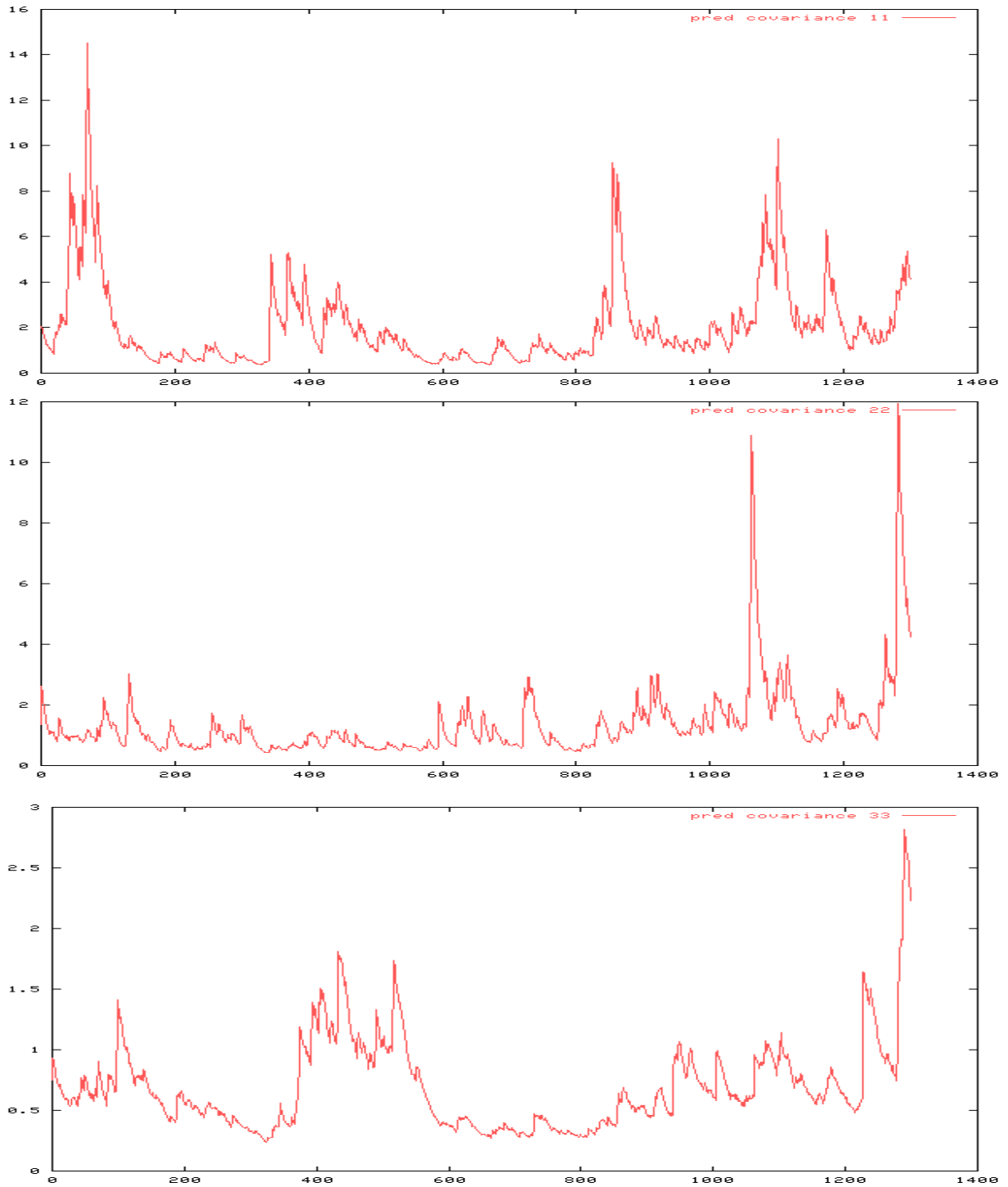
17.077 6.718 18.563 9.736

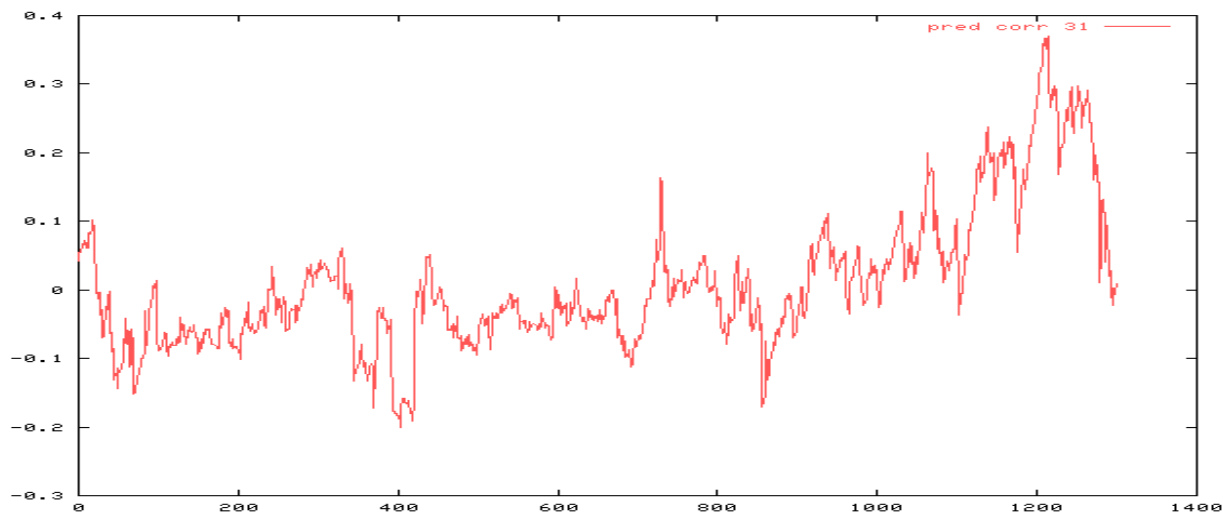
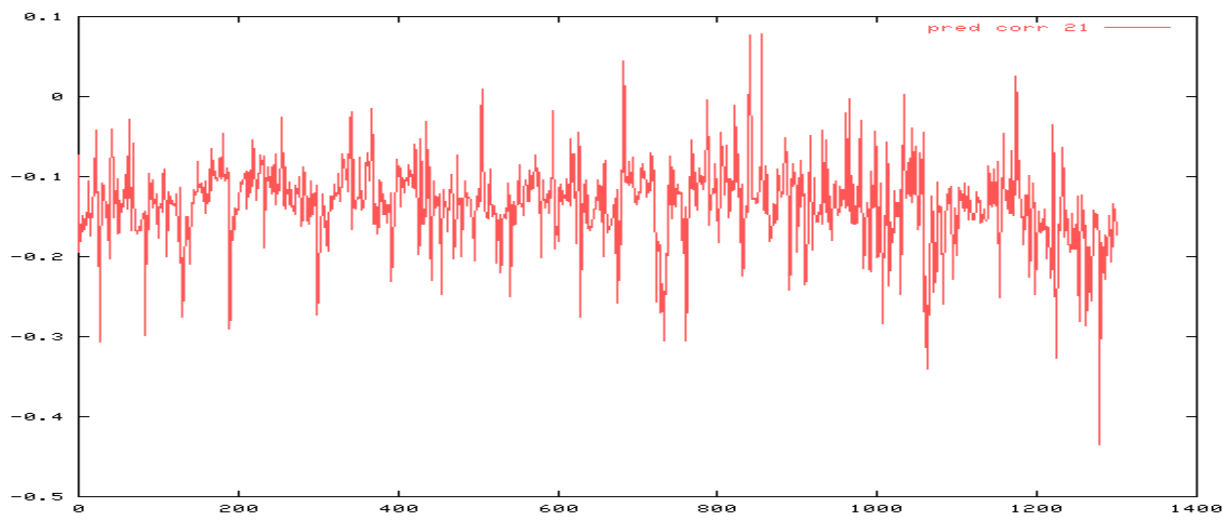
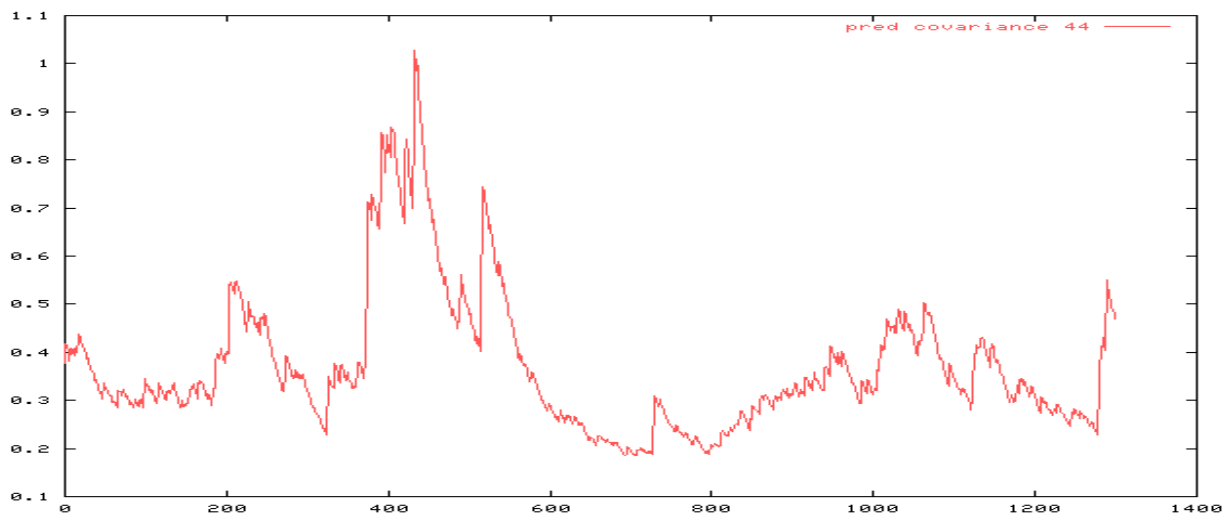
8.760 18.563 3.270 8.525

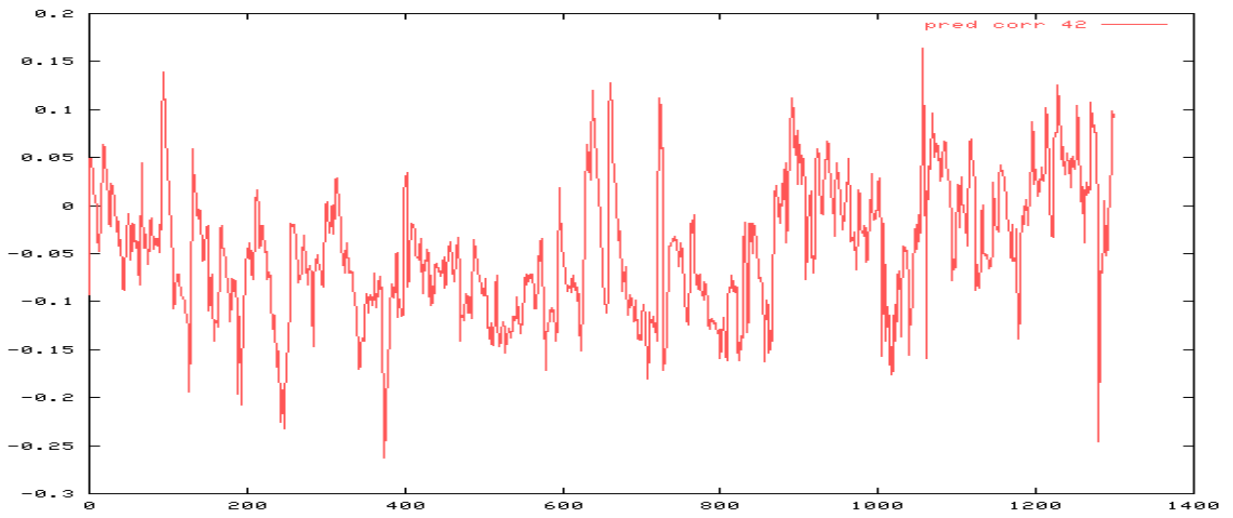
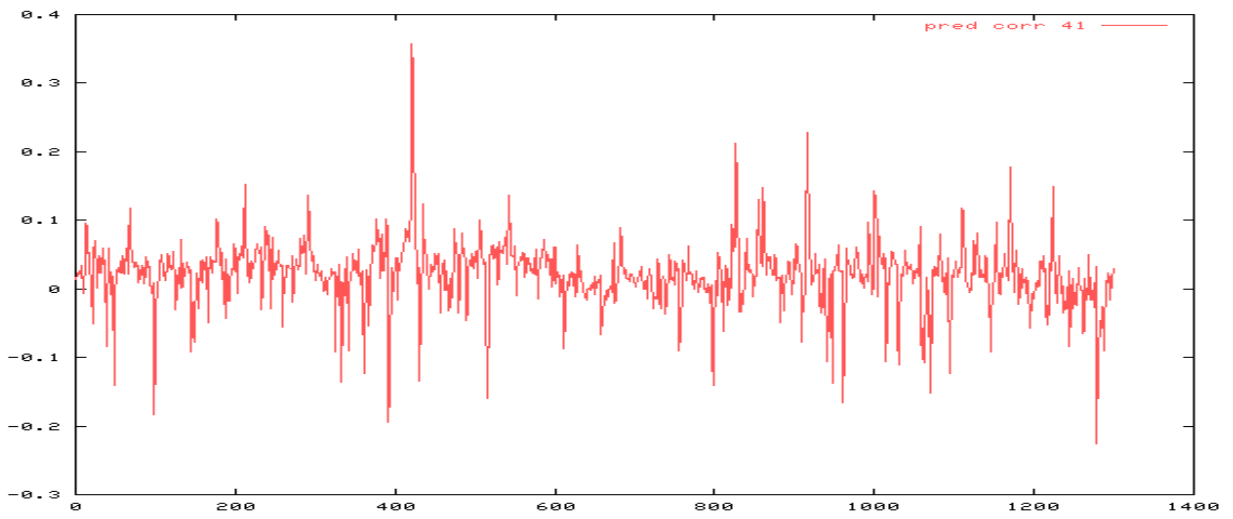
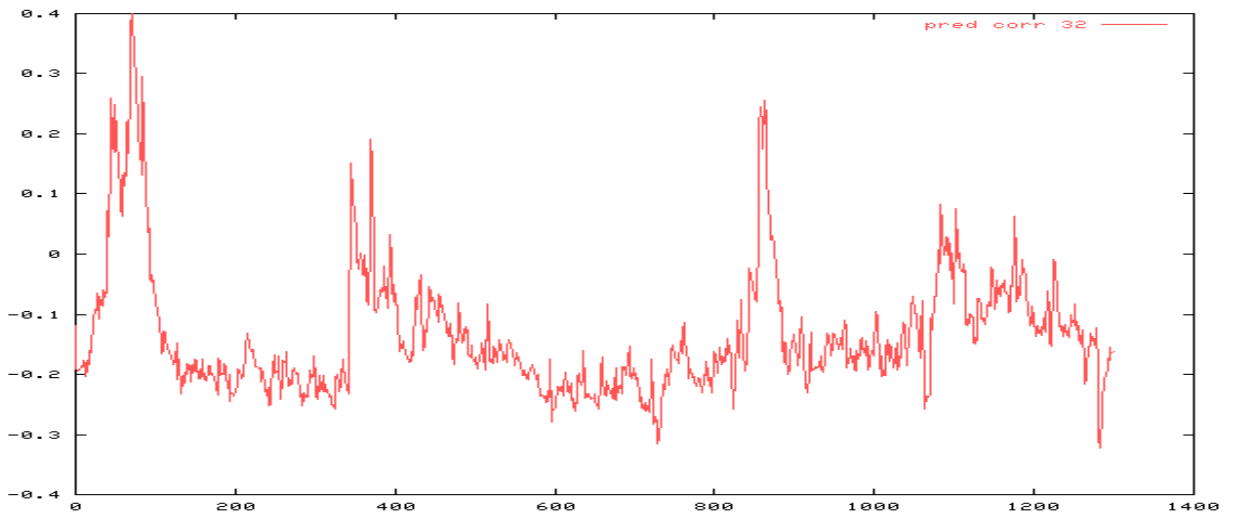
10.487 9.736 8.525 10.253

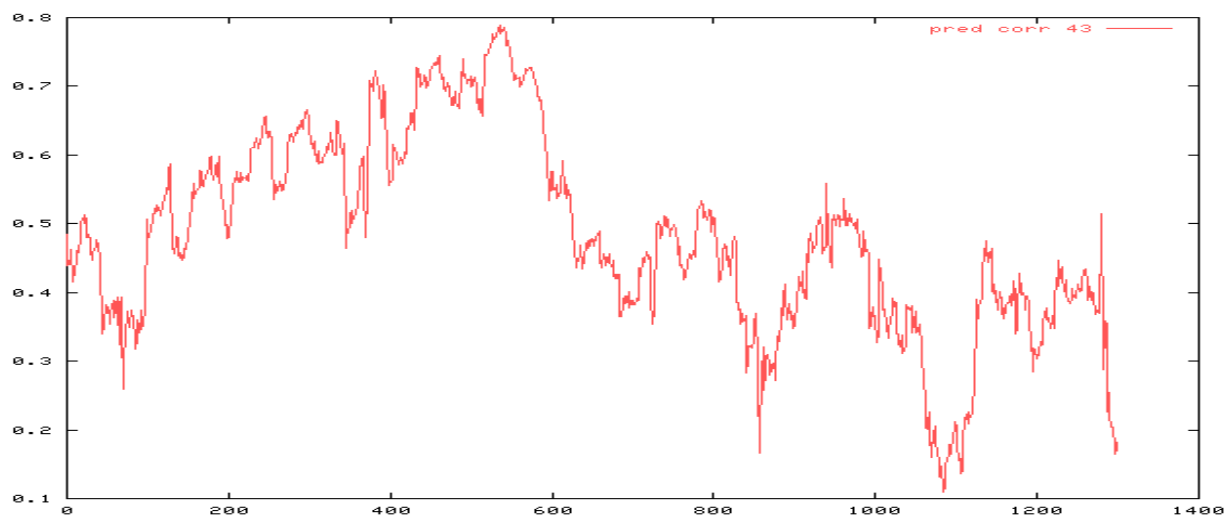
While the model 1,1,2,1a produced almost as high a log-likelihood value as model 1,2,1,1a, the superior performance of the latter model with respect to the Box-Ljung statistic might prompt us to consider it the model of choice.

The following plots show the predicted values for the and the diagonal variance terms.









## Input Format

By default the stand alone version of the model attempts to read in the data from a file named mgarch.dat This can be changed by a command line option. a reasonable command line option would be

```
mgarch -ind datafile -nox -nohess
```

The command

```
mgarch -?
```

will print out a list of command line options. Part of a data file is shown below. The first line describes the data and specifies the form of the model. The delta flag determines whether the parameters which measure asymmetric response in the ARCH component of the model are estimated. The robustness number controls the amount of robustness in the likelihood function. A value between 0.0 and 0.5 is probably appropriate. A value of 10,000 is used to indicate missing values in the data.

```
# number of    dimension  p q r s delta robustness
# observations                flag
1301          4          0 0 1 1  0    0
-0.473592    -0.30815    -0.199577    -0.154677
0.140859    -0.256788    -0.823379    -0.947582
-0.80579    -0.833361    2.439394    1.208645
```



-1.542773	-0.855767	0.469603	-0.433346
10000	10000	1.445218	0.462298
6.014853	4.964597	-0.189343	-0.231408
-1.064758	-1.700819	-3.143447	0.62605
-0.608465	-2.618972	1.641306	2.127487
-5.242424	2.902805	2.60543	-0.668981
2.205787	2.026769	-1.42811	-0.141505
// .....			
10000	10000	-1.072871	0.365977
-0.208759	1.51892	-0.59516	-0.029556
-2.413508	-2.578193	2.045828	-0.2362
0.890598	0.119672	-0.415587	0.029485
-2.797967	0.943489	-1.377787	0.283592
1.405865	1.915963	-0.696567	0.450668
10000	10000	-0.31709	0.255885
2.971906	-1.704494	0.835319	0.286408
-3.451449	1.233715	-1.144007	-0.322157
1.342827	0.376409	0.279213	0.226602

## Output Files

Since the model produces a lot of output it is a good idea to run it its own directory so that files can be easily deleted. The independent variables of the optimization are in a file named mgarch.par (mgarch.bar is an equivalent binary file.) A more user friendly report is in the file mgarch.rep. The estimated covariances and correlations are in files named covar.XX and correl.XX

The model selection criteria have identified the mode 1.1.1ai as the best of the models considered for these data.

Some parameters of interest are:

# alpha:

0.394461 0.538978 1.19337 0.969918

# A1:

-0.0531276 0.772529 -0.187692 -0.131215

```

0.0898897 -0.399746 -0.142294 -0.106079
0.0740065 0.248345 -0.0629680 -0.212928
0.0918460 -0.0575289 -0.0700786 0.0537302
# B1:
-0.00719450 -0.344793 0.115020 0.00516664
-0.0943230 0.474330 0.147845 0.0936166
-0.0860047 -0.243294 0.0187986 0.217280
-0.0815394 0.0843289 0.00782384 -0.0539808
# F:
-0.109526 -0.0292127 -0.122395 0.0548869
0.000332929 -0.0964482 0.0153865 -0.0346829
-0.0148848 -0.0146167 -0.117961 -0.0529385
-0.00504663 -0.000547068 0.00413882 -0.133956
# G:
0.930026 -0.269741 0.136401 0.427047
-0.0345549 -0.981606 0.00281003 -0.00411475
0.0976783 -0.0132467 -0.976596 0.0306139
0.117971 -0.0134465 0.00647385 -0.955173

```

For the four parameters  $\alpha_i$  a value  $< 1$  indicates that negative values seem to have a larger effect on changes in the covariance structure than positive ones. This effect seems to be much larger in the dollar cross rates than in the stock exchanges indices.

## The code for the BEKKGARCH model

The code for the BEKKGARCH model follows. Additional comments have been added to the code.

```

DATA_SECTION
// This section describes the data inputs to the model.
// By default they are read in from the file bekkgarch.dat.
init_int na // number of time periods
init_int m // dimension of the vector time series
init_int p // degree of autoregression must be >=0
init_int q // degree of moving average mult be >=0
init_int ra // degree of arch must be >=0
init_int sg // degree of arch must be >=0
init_int delta_switch // turns on asymmetric response to shocks
init_number robustness // amount of robustness probably something

```

```

        // between 0 and .05 is right
int n
int msquared
!! n=na-p; // number of obs for conditional likelihood
init_matrix cY(-p+1,n,1,m) // the vector time series of observations
int nmiss
LOC_CALCS
msquared=m*m;
int ii=0;
int j;
int i;
for (i=-p+1;i<=n;i++)
    for (j=1;j<=m;j++)
        if (cY(i,j)==10000) ii++;
nmiss=ii;
END_CALCS
ivector rowmiss(1,nmiss)
ivector colmiss(1,nmiss)
LOC_CALCS
ii=1;
for (i=1;i<=n;i++)
    for (j=1;j<=m;j++)
        if (cY(i,j)==10000) {
            rowmiss(ii)=i;
            colmiss(ii)=j;
            ii++;
        }
END_CALCS
int m1
int beginSigma
matrix Idm(1,m,1,m)
ivector beginF(1,ra)
ivector beginG(1,sg)
ivector beginA(1,p)
ivector beginB(1,q)
int nstart
LOC_CALCS
nstart=0;
if (nmiss>0) nstart=1;
m1=m*(m+1)/2; // "size" of n x n symmetric matrix
Idm=identity_matrix(1,m);
if (p) beginA.fill_seqadd(1+nstart,1);
if (q) beginB.fill_seqadd(p+1+nstart,1);
if (ra) beginF.fill_seqadd(p+q+1+nstart,1);
if (sg) beginG.fill_seqadd(p+q+1+nstart,1);
beginSigma=p+q+1+nstart;
END_CALCS
PARAMETER_SECTION
LOC_CALCS
int mm=m;
int dstart;
if (delta_switch>0)
    dstart=p+q+2+nstart;
else
    dstart=-1;
END_CALCS
// the initial values for the time series and disturbance as
// estimated parameters

```

```

init_bounded_vector mudev(1,m,-100,100,-1)
init_bounded_vector delta(1,m,.1,1.9,dstart)
vector mu(1,m)
vector esd(1,m)
vector muemp(1,m) // empirical covariance matrix
matrix Y(-p+1,n,1,m) // the vector time series of observations
init_matrix_vector A1(1,p,1,mm,1,mm,beginA) // pars for the AR coff matrices
3darray A(1,p,1,m,1,m) // pars for the AR coff matrices
init_matrix_vector B1(1,q,1,mm,1,mm,beginB) // pars for the MA coff matrices
3darray B(0,q,1,m,1,m) // has the additional B(0)=Id
3darray Bt(0,q,1,m,1,m) // has the additional B(0)=Id
4darray cov(1,n,0,q,1,m,1,m) // the m x m blocks for the covariance
3darray TB_S(0,q,1,m,1,m)
matrix Omega(1,m,1,m)
3darray B_S(0,q,1,m,1,m)
init_bounded_vector v_Sigma(1,m1,-10,10.1,beginSigma); // pars for Sigma
matrix Semp(1,m,1,m)
matrix SSemp(1,m,1,m)
matrix ch_Sigma(1,m,1,m)
init_bounded_vector_vector Fcoff(1,ra,1,msquared,-1.000,1.0,beginF)
3darray F(1,ra,1,m,1,m)
3darray tF(1,ra,1,m,1,m)
init_bounded_vector_vector Gcoff(1,sg,1,msquared,-.98,.98,beginG)
LOC_CALCS
if (ra)
{
  int mmin,mmax;
  mmin=Fcoff(1).indexmin();
  mmax=Fcoff(1).indexmax();
  for (int ij=mmin;ij<=mmax;ij++) if (value(Fcoff(1)(ij))==0.0)
    Fcoff(1)(ij)=0.02;
}
if (sg)
{
  int mmin,mmax;
  mmin=Gcoff(1).indexmin();
  mmax=Gcoff(1).indexmax();
  for (int ij=mmin;ij<=mmax;ij++) if (value(Gcoff(1)(ij))==0.0)
    Gcoff(1)(ij)=0.001;
}
END_CALCS
3darray G(1,sg,1,m,1,m)
3darray tG(1,sg,1,m,1,m)
3darray Sigma(1,n,1,m,1,m)
init_bounded_vector missvals(1,nmiss,-5.0,5.0);
vector arpart(1,m)
matrix r(1,n,1,m)
3darray rr(1,n,1,m,1,m)
vector vecr(1,n*m) // VEC[r]
vector y(1,n*m)
number ldet
objective_function_value f
matrix Yv(-p+1,n,1,m) // after subtracting off the mean
!! int q1m=(q+1)*m;
!!CLASS banded_symmetric_dvar_matrix S(1,n*m,q1m);
PROCEDURE_SECTION
int t; int i; int j;
fill_matrices_with_independent_parameters();

```

```

Y=cY;
add_missing_values();
calculate_time_series_mean();
calculate_the_residuals();
calculate_the_empirical_covariance();
SSemp=get_initial_sigma();
dvariable fpen=calculate_the_sub_variances_BEKK();
calculate_the_sub_covariances();
calculate_the_covariance_matrix();
int ierr=0;
// choleski decomposition of a banded symmetric matrix
// produces a banded lower triangular matrix
dvariable fpen1=0.0;
banded_lower_triangular_dvar_matrix blt=choleski_decomp_positive(S,
    1.e-6,fpen1);
fpen+=fpen1;
// solve for y=inv(blt)*vecr
y=solve(blt,vecr);
int ss=0;
dvariable lno=ln_det(Sigma(1),ss);
f+=norm2(log(delta));
for (i=1;i<=q;i++) f+=norm2(B1(i));
f+=norm2(v_Sigma);
for (i=1;i<=ra;i++) f+=norm2(F(i));
for (i=1;i<=sg;i++) f+=norm2(G(i));
dvariable lndet=0.0;
for (i=1;i<=n*m;i++) lndet+=log(blt(i,i));
// robust log-likelihood function -- mixture of normal and
// tiny bit of cauchy
dvar_vector y2= square(y);
if (robustness>1.e-20)
    f+= lndet - sum(log(mfexp(-0.5*y2)+robustness/(1.0+y2)));
else
    f+= lndet - sum(log(mfexp(-0.5*y2)+.0001/(1.0+y2)));

f+=fpen;
(*ad_printf)("f = %lf\n",value(f));
FUNCTION fill_matrices_with_independent_parameters
int ii=1; int i=1; int iii;
double d=sqrt(0.1);
if (!sg) d=1.0;
ch_Sigma.initialize();
// this is the choleski decomp parameterization of the
// covariance matrix
for (i=1;i<=m;i++)
    for (int j=1;j<=i;j++) {
        if (i==j)ch_Sigma(i,i)+=d;
        ch_Sigma(i,j)+=v_Sigma(ii++);
    }
for (iii=1;iii<=ra;iii++) {
    if (iii==1 || active(Fcoeff(iii))) {
        ii=1;
        F(iii).initialize();
        tF(iii).initialize();
        for (i=1;i<=m;i++) {
            for (int j=1;j<=m;j++)
                F(iii)(i,j)=Fcoeff(iii)(ii++);
        }
    }
}

```

```

    }
    tF(iii)=trans(F(iii));
}

for (iii=1;iii<=sg;iii++) {
    if (iii==1 || active(Gcoff(iii))) {
        ii=1;
        G(iii).initialize();
        tG(iii).initialize();
        for (i=1;i<=m;i++) {
            for (int j=1;j<=m;j++) {
                G(iii)(i,j)=Gcoff(iii)(ii++);
            }
            if (iii==1) G(iii)(i,i)+=0.90;
        }
    }
    tG(iii)=trans(G(iii));
}
B.initialize();
A.initialize();
// B(0) is the identity matrix
B(0)=Idm;
for (i=1;i<=p;i++) A(i)=A1(i);
for (i=1;i<=q;i++) B(i)=B1(i);
for (i=0;i<=q;i++) Bt(i)=trans(B(i));

FUNCTION calculate_the_residuals
int t; int j;
mu=muemp+mudev;
for (t=-p+1;t<=0;t++) Yv(t)=Y(t)-mu;
for (t=1;t<=n;t++) {
    Yv(t)=Y(t)-mu;
    calculate_autoregressive_part(t);
    r(t)=Yv(t)-arpart;
}
int ii=0;
// this corresponds to the VEC operator
for (int i=1;i<=n;i++)
    for (j=1;j<=m;j++) vecr(++ii)=r(i,j);

FUNCTION void calculate_the_residuals2(dvar_matrix& e)
int t; int j;
mu=muemp+mudev;
for (t=-p+1;t<=0;t++) Yv(t)=Y(t)-mu;
for (t=1;t<=n;t++) {
    Yv(t)=Y(t)-mu;
    calculate_autoregressive_part(t);
    e(t)=Yv(t)-arpart;
    for (j=1;j<=q;j++) {
        if (t<=j) break;
        e(t)-=B(j)*e(t-j);
    }
}
}

FUNCTION calculate_the_sub_covariances
int i; int k; int l;
int qq=0;
for ( l=1;l<=q;l++) {

```

```

        if (!active(B1(1))) break;
        qq=1;
    }
    cov.initialize();
    for (i=1;i<=n;i++) {
        for (int l=0;l<=qq;l++) {
            if (i<=l) break;
            for (int k=0;k<=qq-l;k++) {
                int ilk=i-l-k;
                if (ilk<1) ilk=1;
                cov(i,l)+=B(1+k)*Sigma(ilk)*Bt(k);
            }
        }
    }
}

FUNCTION calculate_the_empirical_covariance
int i;
Semp.initialize();
ivector sgn(1,m);
esd.initialize();
for (i=1;i<=n;i++) {
    esd+=square(r(i));
}
esd/=n;
esd=sqrt(esd);
if (active(delta)) {
    dvar_vector mult_neg=elem_div(esd,delta);
    dvar_vector mult_pos=elem_prod(esd,delta);
    for (i=1;i<=n;i++) {
        sgn.initialize();
        dvar_vector sr=sfabs(elem_div(r(i),esd));
        for (int j=1;j<=m;j++)
            if (r(i,j)<0)
                sr(j)=-sr(j)*mult_neg(j);
            else
                sr(j)=sr(j)*mult_pos(j);
        rr(i)=outer_prod(sr,sr);
    }
    Semp=empirical_covariance(r);
}
else
{
    for (i=1;i<=n;i++) {
        rr(i)=outer_prod(r(i),r(i));
        Semp+=rr(i);
    }
    Semp/=n;
}
for (int j=1;j<=m;j++)
    esd(j)=sqrt(Semp(j,j));

FUNCTION dvariable calculate_the_sub_variances_diagonal_vector_garch(void)
int i; int k; int ii; int jj;
dvar_vector norms(1,n);
dvariable fpen=0.0;
dvariable fpen1;
Omega=ch_Sigma*SSemp*trans(ch_Sigma);

```

```

Sigma.initialize();
// set the first Sigma equal to the empirical covariance
int rsmx=mymax(ra,sg);
Sigma(1)=SSemp;
//cout << Sigma(1) << endl;
dvar_matrix SS=scale(Sigma(1),esd);
//cout << SS << endl;
fpen+=positivize_sigma(SS);
//cout << SS << endl;
dvariable ns=norm(SS);
norms(1)=ns;
fpen1=0.0;
dvariable bn=mf_upper_bound(ns,1000.0,fpen1);
if (fpen1>0.0) {
    SS*=(bn/ns);
    fpen+=fpen1;
}
Sigma(1)=unscale(SS,esd);
for (i=2;i<=rsmx;i++) {
    Sigma(i)=Sigma(1);
    norms(i)=norms(1);
}

int mmin=Sigma(1).indexmin();
int mmax=Sigma(1).indexmax();
dvar_vector s(mmin,mmax);
for (i=rsmx+1;i<=n;i++) {
    Sigma(i)=0omega;
    if (ra) Sigma(i)+=elem_prod(F(1),rr(i-1));
    for (ii=2;ii<=ra;ii++) {
        if (active(Fcoeff(ii)))
            Sigma(i)+=elem_prod(F(ii),rr(i-ii));
    }

    if (sg) Sigma(i)+=elem_prod(G(1),Sigma(i-1));
    for (ii=2;ii<=sg;ii++) {
        if (active(Gcoeff(ii)))
            Sigma(i)+=elem_prod(G(ii),Sigma(i-ii));
    }

    // "positivize" the
    // correlation matrix
    dvar_matrix SS=scale(Sigma(i),esd);
    fpen+=positivize_sigma(SS);
    dvariable ns=norm(SS);
    norms(i)=ns;
    fpen1=0.0;
    dvariable bn=mf_upper_bound(ns,1000.0,fpen1);
    if (fpen1>0.0) {
        SS*=(bn/ns);
        fpen+=fpen1;
    }
    Sigma(i)=unscale(SS,esd);
}
dvector trend(1,n);
trend.fill_seqadd(-1,2.0/(n-1));
cout << "norms*trend/norm(norms)" << endl;
dvariable npen=norms*trend/norm(norms);

```



```

cout << norms*trend/norm(norms) << endl;
fpen+=npen;
if (fpen>1.0)
    cout << " fpen = " << fpen << endl;
return fpen;

FUNCTION dvariable calculate_the_sub_variances_BEKK(void)
    int i; int k; int ii; int jj;
    dvar_vector norms(1,n);
    dvariable fpen=0.0;
    dvariable fpen1;
    Omega=ch_Sigma*SSemp*trans(ch_Sigma);
    Sigma.initialize();
    // set the first Sigma equal to the empirical covariance
    int rsmx=mymax(ra,sg);
    Sigma(1)=SSemp;
    dvar_matrix SS=scale(Sigma(1),esd);
    fpen+=positivize_sigma(SS);
    dvariable ns=norm(SS);
    norms(1)=ns;
    fpen1=0.0;
    dvariable bn=mf_upper_bound(ns,1000.0,fpen1);
    if (fpen1>0.0) {
        SS*=(bn/ns);
        fpen+=fpen1;
    }
    Sigma(1)=unscale(SS,esd);
    for (i=2;i<=rsmx;i++) {
        Sigma(i)=Sigma(1);
        norms(i)=norms(1);
    }

    int mmin=Sigma(1).indexmin();
    int mmax=Sigma(1).indexmax();
    dvar_vector s(mmin,mmax);
    for (i=rsmx+1;i<=n;i++) {
        Sigma(i)=Omega;
        if (ra) Sigma(i)+=F(1)*rr(i-1)*tF(1);
        for (ii=2;ii<=ra;ii++) {
            if (active(Fcoff(ii)))
                Sigma(i)+=F(ii)*rr(i-ii)*tF(ii);
        }

        if (sg) Sigma(i)+=G(1)*Sigma(i-1)*tG(1);
        for (ii=2;ii<=sg;ii++) {
            if (active(Gcoff(ii)))
                Sigma(i)+=G(ii)*Sigma(i-ii)*tG(ii);
        }

        // "positivize" the
        // correlation matrix
        dvar_matrix SS=scale(Sigma(i),esd);
        fpen+=positivize_sigma(SS);
        dvariable ns=norm(SS);
        norms(i)=ns;
        fpen1=0.0;
        dvariable bn=mf_upper_bound(ns,1000.0,fpen1);
        if (fpen1>0.0) {

```

```

        SS*=(bn/ns);
        fpen+=fpen1;
    }
    Sigma(i)=unscale(SS,esd);
}
dvector trend(1,n);
trend.fill_seqadd(-1,2.0/(n-1));
cout << "norms*trend/norm(norms)" << endl;
dvariable npen=norms*trend/norm(norms);
cout << norms*trend/norm(norms) << endl;
fpen+=npen;
if (fpen>1.0)
    cout << " fpen = " << fpen << endl;
{
    //ofstream ofs("sigma");

    //for (int i=1;i<=n;i++)
        //ofs << Sigma(i) << endl << endl;
}
return fpen;

FUNCTION dvar_matrix scale(dvar_matrix& M,dvar_vector& sd)
    int mmin=sd.indexmin();
    int mmax=sd.indexmax();
    dvar_matrix SM(mmin,mmax,mmin,mmax);
    for (int i=mmin;i<=mmax;i++)
        for (int j=mmin;j<=mmax;j++)
            SM(i,j)=M(i,j)/(sd(i)*sd(j));
    return SM;

FUNCTION dvar_matrix unscale(dvar_matrix& M,dvar_vector& sd)
    int mmin=sd.indexmin();
    int mmax=sd.indexmax();
    dvar_matrix SM(mmin,mmax,mmin,mmax);
    for (int i=mmin;i<=mmax;i++)
        for (int j=mmin;j<=mmax;j++)
            SM(i,j)=M(i,j)*(sd(i)*sd(j));
    return SM;

FUNCTION dvar_matrix get_initial_sigma(void)
    int i,j,k,l,ll,m2,r,s;
    m2=m*m;
    dvar_matrix M(1,m2,1,m2);

    dvar_vector v=VEC(Semp);
    M=identity_matrix(1,m2);
    for (ll=1;ll<=q;ll++)
    {
        for (i=1;i<=m;i++)
        {
            for (j=1;j<=m;j++)
            {
                int col=(i-1)*m+j;
                for (r=1;r<=m;r++)
                {
                    for (s=1;s<=m;s++)
                    {
                        int row=(r-1)*m+s;

```

```

        M(row,col)+=B(l1)(r,i)*B(l1)(s,j);
    }
}
}
}
v=solve(M,v);
dvar_matrix tmp= MAT(v,m,m);
return tmp;

FUNCTION calculate_the_covariance_matrix
int ioffset; int joffset; int i1; int i; int j1;
int k; int l;
int qq=0;
for ( l=1;l<=q;l++) {
    if (!active(B1(l))) break;
    qq=l;
}
S.initialize();
for (i=1;i<=n;i++) {
    ioffset=(i-1)*m;
    for (int k=0;k<=qq;k++) {
        //if (k>0 && !active(B1)) break;
        joffset=(i-k-1)*m;
        if (joffset<0) break;
        for (i1=1;i1<=m;i1++) {
            int up;
            if (k==0)
                up=i1;
            else
                up=m;
            for (j1=1;j1<=up;j1++) {
                int i2=i1+ioffset;
                int j2=j1+joffset;
                S(i1+ioffset,j1+joffset)=cov(i,k,i1,j1);
            }
        }
    }
    if (S(1,1) < 0)
        cout << S(1,1) << endl;
}

FUNCTION void calculate_autoregressive_part(int t)
// The user can put in any (nonlinear) function desired here
arpart.initialize();
for (int j=1;j<=p;j++) arpart+=A(j)*Yv(t-j);

REPORT_SECTION
int i; int ii; int jj, t;
for (ii=1;ii<=m;ii++)
{
    for (jj=1;jj<=ii;jj++)
    {
        ofstream ofs((char*)"covar." + str(ii) +str(jj));
        ofstream ofs1((char*)"correl." + str(ii) +str(jj));
        dvar_matrix Covariance(1,m,1,m);
        for (i=1;i<=n;i++) {
            Covariance=Sigma(i);

```

```

        for(int j=1;j<=q;j++)
            if ( (i-j)>0 ) Covariance+=B(j)*Sigma(i-j)*trans(B(j));
        ofs << Covariance(ii,jj) << endl;
        ofs1 << Covariance(ii,jj)/
            sqrt(Covariance(ii,ii)*Covariance(jj,jj))<< endl;
    }
}
}

{
    dvar_matrix ymat=MAT(y,n,m);
    for (int i=1;i<=m;i++) {
        ofstream ofs1((char*)"yres." + str(i));
        dvector tmp(1,n);
        for (t=1;t<=n;t++)
            tmp(t)=value(ymat(t,i));
        ivector hist=histogram(-20,20,81,tmp);
        ofs1 << column_print(hist) << endl;
    }
}
report << "The means" << endl;
report << mu << endl;
for (i=1;i<=p;i++) {
    report << "A("<< i << ")" << endl;
    report << setfixed() << setprecision(3) << A(i) << endl;
}
report << endl;
for (i=1;i<=q;i++) {
    report << "B("<< i << ")" << endl;
    report << setfixed() << setprecision(3) << B(i) << endl;
}
report << endl;
report << "delta" << endl;
report << setfixed() << setprecision(3) << delta << endl;
report << endl;
report << "Omega" << endl;
report << setfixed() << setprecision(3) << Omega << endl;
report << endl;
for (i=1;i<=ra;i++) {
    report << "F("<< i << ")" << endl;
    report << setfixed() << setprecision(3) << F(i) << endl;
}
report << endl;
for (i=1;i<=sg;i++) {
    report << "G("<< i << ")" << endl;
    report << setfixed() << setprecision(3) << G(i) << endl;
}
report << endl;
//report << setfixed() << setw(8) << setprecision(1) << S << endl;
{ // calculate predicted observations for next 20 time periods
    // for graphs results are in t.1 t.2 etc
    int npreds=20;
    dvar_matrix e(1,n,1,m);
    calculate_the_residuals2(e);

    dvar_matrix Z(n+1,n+npreds,1,m);
    Z.initialize();
}
}
}

```

```

for (int t=n+1;t<=n+npreds;t++) {
    Z(t)+=mu;
    for (int i=1;i<=p;i++) {
        if (t-i>n)
            Z(t)+=A(i)*(Z(t-i)-mu);
        else
            Z(t)+=A(i)*(Y(t-i)-mu);
    }
    for (i=1;i<=q;i++) {
        if (t-i<=n && t-i>0)
            Z(t)+=B(i)*e(t-i);
    }
}
for (i=1;i<=m;i++) {
    ofstream ofs1((char*)"pred" + str(i));
    for (t=-p+1;t<=n;t++)
        ofs1 << Y(t,i) << endl;
    for (t=n+1;t<=n+npreds;t++)
        ofs1 << Z(t,i) << endl;
}
}
dmatrix T(1,m,1,m);
dmatrix chi(1,m,1,m);
T.initialize();
dmatrix Aut(1,m,1,m);
Aut.initialize();
const int K=10;
d3_array gamma(1,K,1,m,1,m);
dmatrix cr(1,n,1,m);
for (i=1;i<=n;i++)
{
    cr(i)=value(y((i-1)*m+1,i*m).shift(1));
    T+=outer_prod(cr(i),cr(i));
}
T=T/n;
for (i=2;i<=n;i++)
{
    Aut+=outer_prod(cr(i-1),cr(i));
}
Aut=Aut/(n-1);
for (i=1;i<=m;i++)
{
    for (int j=1;j<=m;j++)
    {
        Aut(i,j)/=sqrt(T(i,i)*T(j,j));
    }
}
gamma.initialize();
for (int j=1;j<=m;j++)
{
    for (int k=1;k<=m;k++)
    {
        for (int l=1;l<=10;l++)
        {
            double tmp=0;
            for (i=1;i<=n-l;i++)
            {
                gamma(l,j,k)+=(cr(i,j)*cr(i,k)-T(j,k))*(cr(i+l,j)*cr(i+l,k)-T(j,k));
            }
        }
    }
}

```

```

        tmp+=square(cr(i,j)*cr(i,k)-T(j,k));
    }
    gamma(l,j,k)/=tmp;
}
}
}

chi.initialize();
for (int l=1;l<=K;l++)
{
    chi+=n*(n+2)/(n-1)*square(gamma(l));
}

report << "Covariance of standardized residuals" << endl;
report << T << endl;
report << "Lag 1 autocorellation of standardized residuals" << endl;
report << Aut << endl;
report << "Ljung Box statistic based on chi squared with " << K
    << " degrees of freedom" << endl;
report << chi << endl;

FUNCTION add_missing_values
for (int ii=1;ii<=nmiss;ii++) {
    Y(rowmiss(ii),colmiss(ii))=missvals(ii);
}
ofstream ofs("testy");
ofs << Y << endl;

FUNCTION calculate_time_series_mean
muemp.initialize();
for (int i=-p+1;i<=n;i++) muemp+=Y(i);
muemp/=(n+p);

FUNCTION dvariable positivize_sigma(dvar_matrix& TS)
int ii,jj;
dvariable fpen=0.0;
int mmin=TS.indexmin();
int mmax=TS.indexmax();
dvar_vector s(mmin,mmax);
for (ii=mmin;ii<=mmax;ii++)
    s(ii)=sqrt(posfun(TS(ii,ii),1.e-3,fpen));
for (ii=mmin;ii<=mmax;ii++)
    for (jj=mmin;jj<=mmax;jj++)
        TS(ii,jj)/=(s(ii)*s(jj));
TS=positive_definite_matrix(TS,.3,fpen);
for (ii=mmin;ii<=mmax;ii++)
    for (jj=mmin;jj<=mmax;jj++)
        TS(ii,jj)*=(s(ii)*s(jj));
return fpen;

GLOBALS_SECTION
// some C++ compilers don't supply this!
int mymax(int x,int y)
{
    if (x>y)
        return x;
    else
        return y;
}

```

```
}  
  
TOP_OF_MAIN_SECTION  
  
    ofstream ofs("Error.log");  
    arrmblsize=5000000;  
    gradient_structure::set_GRADSTACK_BUFFER_SIZE(560000);  
    gradient_structure::set_CMPDIF_BUFFER_SIZE(15000000);  
    gradient_structure::set_MAX_NVAR_OFFSET(1000);
```





# Chapter 7

## The Kalman filter

### The Kalman Filter

The Kalman filter is a device for estimating parameters in a class of “time-series” like models which are put into state-space form. We have used the notation from Harvey, chapter 3. The general state space form is an multivariate time series

$$y_t = Z_t \alpha_t + d_t + \epsilon_t$$

where  $Z_t$  is an  $N \times m$  matrix,  $d_t$  is an  $N$  dimensional vector,  $y_t$  is an  $N$  dimensional vector and  $\epsilon_t$  is a set of serially uncorrelated  $N$  dimensional random vectors with mean 0 and correlation  $H_t$ . The elements of  $\alpha_t$  are not observable but are assumed to be generated by a first order Markov process

$$\alpha_t = T_t \alpha_{t-1} + c_t + R_t \eta_t$$

where  $T_t$  is an  $m \times m$  matrix,  $c_t$  is an  $m \times 1$  vector,  $R_t$  is an  $m \times g$  matrix and  $\eta_t$  is a  $g \times 1$  vector of serially uncorrelated random vectors with mean 0 and covariance matrix  $H_t$ . The specification of the state space system is completed by two further assumptions: 1. The initial state vector  $\alpha_0$  has a mean of  $a_0$  and a variance of  $P_0$ . 2. The random vectors  $\epsilon_t$  and  $\eta_t$  are uncorrelated with each other and uncorrelated with the initial state.

In applications of the model many of the parameters  $Z_t$ ,  $d_t$ ,  $H_t$ ,  $T_t$ ,  $c_t$ ,  $R_t$ , and  $Q_t$  may be independent of  $t$  in which case we will write them without the subscript. Also  $R$  may be the identity matrix in which case we will omit it.

As a simple example of such a model consider the (two dimensional) random walk observed with error example considered below.

$$\begin{aligned} \alpha_t &= \alpha_{t-1} + \eta_t \\ y_t &= \alpha_t + \epsilon_t \end{aligned} \tag{7.1}$$

For this model the following parameters are fixed.

$$T = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \quad Z = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \quad R = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \quad d = (0, 0) \quad c = (0, 0)$$

while the covariance matrices  $Q$  and  $H$  are estimated. Their true values used for simulating the data were. The initial value of  $a$  is  $(0, 0)$ .

$$Q = \begin{pmatrix} 1 & 0.8 \\ 0.8 & 1 \end{pmatrix} \quad H = \begin{pmatrix} 3 & -2.5 \\ -2.5 & 3 \end{pmatrix}$$

## Equations for the Kalman filter

For a moment go back to the general state space model. Given  $a_0, P_0$  we recursively calculate the a number of quantities via the relationships

$$\begin{aligned} a_{t|t-1} &= T_t a_{t-1} + c_t \\ P_{t|t-1} &= T_t P_{t-1} T_t' + R_t Q_t R_t' \\ v_t &= y_t - Z_t a_{t|t-1} - d_t \\ F_t &= Z_t P_{t|t-1} Z_t' + H_t \\ a_t &= a_{t|t-1} - P_{t|t-1} Z_t' F_t^{-1} v_t \\ P_t &= P_{t|t-1} - P_{t|t-1} Z_t' F_t^{-1} Z_t P_{t|t-1} \end{aligned} \tag{7.2}$$

The log likelihood function for the models parameters is given by

$$\log L = -\frac{NT}{2} \log 2\pi - 0.5 \sum_{t=1}^T \log |F_t| - 0.5 \sum_{t=1}^T v_t F_t^{-1} v_t$$

The TPL file for the random walk kalman filter code follows

```
DATA_SECTION
  init_int nt
  init_int N
  init_int m
  int m1
  init_matrix Y(1,nt,1,N)
  matrix P0(1,m,1,m)
  !! P0.initialize();
  !! m1=m*(m+1)/2;
PARAMETER_SECTION
  init_bounded_vector Qcoeff(1,m1,-10.,10.1)
  init_bounded_vector Hcoeff(1,m1,-10.,10.1)
  init_vector a0(1,m)
  matrix T(1,m,1,m)
  matrix TT(1,m,1,m)
  vector d(1,N)
  vector c(1,m)
  matrix chQ(1,m,1,m)
```

```

sdreport_matrix Q(1,m,1,m)
matrix chH(1,N,1,N)
sdreport_matrix H(1,N,1,N)
matrix Z(1,N,1,m)
matrix TZ(1,m,1,N)
objective_function_value f
LOCAL_CALCS
  d.initialize();
  c.initialize();
  Z.initialize();
  Z(1,1)=1; Z(2,2)=1;
  T.initialize();
  T(1,1)=1; T(2,2)=1;
  TZ=trans(Z);
  TT=trans(T);
PROCEDURE_SECTION
  setup_Q();
  setup_H();
  f+=kalman_filter();
  cout << " f = " << f << endl;

FUNCTION setup_Q
  chQ.initialize();
  int ii=1;
  for (int i=1;i<=m;i++)
    for (int j=1;j<=i;j++)
      chQ(i,j)=Qcoeff(ii++);
  Q=chQ*trans(chQ);
FUNCTION setup_H
  chH.initialize();
  int ii=1;
  for (int i=1;i<=N;i++)
    for (int j=1;j<=i;j++)
      chH(i,j)=Hcoeff(ii++);
  H=chH*trans(chH);

FUNCTION dvariable kalman_filter(void)
  dvar3_array P(0,nt,1,m,1,m);
  dvar3_array P1(1,nt,1,m,1,m);
  dvar3_array F(1,nt,1,N,1,N);
  dvar3_array Finv(1,nt,1,N,1,N);
  dvar_matrix Ptemp(1,m,1,m);
  dvar_matrix a(0,nt,1,m);
  dvar_matrix a1(1,nt,1,m);
  dvar_matrix v(1,nt,1,N);
  a(0)=a0;
  P(0)=P0;
  // This is the Kalman filter recursion. The objects tmp1
  // and tmp2 hold common calculations to optimize a bit
  int t;
  for (t=1;t<=nt;t++)
  {
    a1(t)=T*a(t-1)+c;
    P1(t)=T*P(t-1)*TT+Q;
    dvar_vector pred_y=Z*a1(t)+d;
    v(t)=Y(t)-pred_y;
    dvar_matrix tmp1=P1(t)*TZ;
    F(t)=Z*tmp1+H;
  }

```

```

    Finv(t)=inv(F(t));
    dvar_matrix tmp2= tmp1*Finv(t);
    P(t)=P1(t)-tmp2*Z*P1(t);
    a(t)=a1(t)+tmp2*v(t);
}
int sgn=0;
dvariable f=0.0;
for (t=1;t<=nt;t++)
    f+=ln_det(F(t),sgn)+v(t)*Finv(t)*v(t);
return f;
TOP_OF_MAIN_SECTION
arrmblsize=20000000;
gradient_structure::set_CMPDIF_BUFFER_SIZE(3000000);
gradient_structure::set_GRADSTACK_BUFFER_SIZE(1000000);

```

This example was deliberately not optimized as much as it could be in order to retain the flavour of the more general state space problem. For example since  $T$  is the identity matrix and  $c$  is the zero vector the line of code

```
a1(t)=T*a(t-1)+c;
```

reduces to

```
a1(t)=a(t-1);
```

The parameters being estimated are  $a_0$ ,  $Q$ , and  $H$ .

To parameterize the covariance matrices the Choleski decomposition parameterization was used. This ensures that the covariance matrices are positive (semi) definite. The technique can be seen in the function `setup_Q`. The lower triangular matrix `ch_Q` is filled with parameters from a bounded vector

```

FUNCTION setup_Q
chQ.initialize();
int ii=1;
for (int i=1;i<=m;i++)
    for (int j=1;j<=i;j++)
        chQ(i,j)=Qcoeff(ii++);
Q=chQ*trans(chQ); // chQ is the choleski decomposition of Q

```

Notice that the bounded vector `Qcoeff` has slightly asymmetric bounds. This is a simple way to ensure that its initial value is not identically 0 which would lead to a singular covariance matrix.

```
init_bounded_vector Qcoeff(1,m1,-10.,10.1)
```

The model parameters, standard deviations and correlations are reproduced from the standard ADMB report.

index	name	value	std dev	7	8	9	10	11	12	13	14	15	16
7	a0	-1.1682e+00	9.0191e-01	1.000									
8	a0	1.2218e+00	8.6442e-01	0.352	1.000								

```

 9 Q      9.9468e-01 1.0862e-01 0.059 -0.006 1.000
10 Q      7.8808e-01 7.8737e-02 0.038 0.028 0.683 1.000
11 Q      7.8808e-01 7.8737e-02 0.038 0.028 0.683 1.000 1.000
12 Q      8.7279e-01 9.6118e-02 -0.018 0.069 0.185 0.721 0.721 1.000
13 H      3.1352e+00 1.8123e-01 -0.015 -0.007 -0.305 -0.136 -0.136 -0.018 1.000
14 H     -2.7119e+00 1.4922e-01 -0.021 0.001 -0.102 -0.238 -0.238 -0.139 -0.692 1.000
15 H     -2.7119e+00 1.4922e-01 -0.021 0.001 -0.102 -0.238 -0.238 -0.139 -0.692 1.000 1.000
16 H      3.2264e+00 1.7936e-01 0.015 -0.029 -0.031 -0.121 -0.121 -0.249 0.370 -0.698 -0.698 1.000

```

## Parameterizing the covariance matrix parameterizations

The Choleski decomposition parameterization merely ensures that the matrix is positive semi-definite. By adding a small positive number to the diagonal elements one can ensure that the covariance matrix is positive definite and can speed up and improve the stability of the estimation. Of course what is meant by small will depend on the particular problem being considered. A modified form of the routine `setup_Q` follows.

```

FUNCTION setup_Q
  int i;
  chQ.initialize();
  int ii=1;
  for (i=1;i<=m;i++)
    for (int j=1;j<=i;j++)
      chQ(i,j)=Qcoeff(ii++);
  Q=chQ*trans(chQ); // chQ is the choleski decomposition of Q
  for (i=1;i<=m;i++)
    Q(i,i)+=0.1; // make Q positive definite

```

Performing this modification for the present model for both  $Q$  and  $H$  causes the program to converge about twice as fast.



## Chapter 8

# Applying the Laplace approximation to the Generalized Kalman Filter – with an application to Stochastic Volatility Models

Let  $y_i$  be an  $N$  dimensional multivariate time series for  $i = 1, \dots, n$  where  $y_i$  is a random vector with probability density function  $p(y_i|\alpha_i)$ . For each  $i$ , the  $\alpha_i$  are random vectors which satisfy the condition

$$\alpha_i = T_i(\alpha_{i-1}, y_{i-1}) + \eta_i \quad (8.1)$$

where  $\mu_{\eta_i} = 0$  and  $\sigma_{\eta_i}^2 = \sigma_{\eta}^2$ .

Let  $p(\alpha_1)$  be the probability density function for  $\alpha_1$  before  $y_1$  is observed. After observing  $y_1$  we want to calculate the probability distribution of  $\alpha_1$  given  $y_1$ . This is given by

$$p(\alpha_1|y_1) = p(y_1|\alpha_1)p(\alpha_1)/p(y_1) \quad (8.2)$$

where

$$p(y_1) = \int_{-\infty}^{\infty} p(y_1|\alpha_1)p(\alpha_1) d\alpha_1 \quad (8.3)$$

let  $\phi(y_1, \alpha_1) = \log(p(y_1|\alpha_1)p(\alpha_1))$  Let  $\hat{\alpha}_1(y_1) = \max_{\alpha_1} \{\phi(y_1, \alpha_1)\}$ . Approximate  $\phi$  by its second order taylor expansion in  $\alpha_1$  at  $\hat{\alpha}_1$ .

$$\phi(y_1, \alpha_1) \approx \phi(y_1, \hat{\alpha}_1) + D_{\alpha_1 \alpha_1}^2 \phi(y_1, \hat{\alpha}_1(y_1))(\alpha_1 - \hat{\alpha}_1(y), \alpha_1 - \hat{\alpha}_1(y)) \quad (8.4)$$

so that

$$p(y) \approx e^{\phi(y_1, \hat{\alpha}_1(y_1))} \int_{-\infty}^{\infty} \exp \left\{ - ( - D_{\alpha_1 \alpha_1}^2 \phi(y_1, \hat{\alpha}_1(y_1))(\alpha_1 - \hat{\alpha}_1(y), \alpha_1 - \hat{\alpha}_1(y))) \right\} d\alpha_1 \quad (8.5)$$

Making a change of variables and integrating we obtain

$$p(y_1) \approx e^{\phi(y_1, \hat{\alpha}_1(y_1))} (2\pi)^{n/2} | - D_{\alpha_1 \alpha_1}^2 \phi(y_1, \hat{\alpha}_1(y_1)) |^{-1/2} \quad (8.6)$$

This is the Laplace approximation to the integral in (8.3).

If the distribution of  $\alpha_1$  is (multivariate) normal and the distribution of  $y_1|\alpha_1$  is multivariate normal then  $\phi(y_1, \alpha_1)$  is a quadratic function of  $\alpha_1$  so that the Laplace approximation is exact. The advantage of the Laplace approximation is that it can be employed for non normal distributions.

To illustrate this advantage consider the simple one dimensional case where  $\alpha_1$  has a (univariate) normal distribution with mean 0 and variance  $\sigma_\alpha^2$ . Assume that the distribution of  $y_1|\alpha_1$  is a fat-tailed distribution which is a mixture of 0.95 normal distribution and 0.05 cauchy distribution. Then

$$\phi(y_1, \alpha_1) = \log \left[ 0.95 \exp(-0.5(y_1 - \alpha_1)^2 / \sigma_y^2) + 0.05 \sqrt{2/\pi} / (1 + (y_1 - \alpha_1)^2 / \sigma_y^2) \right] - 0.5 \alpha_1^2 / \sigma_\alpha^2 + \text{const}$$

whereas if  $y_1$  is assumed to have a normal distribution

$$\phi(y_1, \alpha_1) = -0.5(y_1 - \alpha_1)^2 / \sigma_y^2 - 0.5 \alpha_1^2 / \sigma_\alpha^2 + \text{const} \quad (8.8)$$

where *const* denotes some constant independent of  $\alpha_1$ . There are two drawbacks to the use of 5.b If the value of  $y_1$  is an outlier from the point of the normal model then it will have too much influence on the mode of the estimate of  $p(\alpha_1|y_1)$ . Also since the variance

$$\sigma_{\alpha_1|y_1}^2 = D_{\alpha_1 \alpha_1}^2 \phi(y_1, \beta_i) \}^{-1} = [1/\sigma_y^2 + 1/\sigma_\alpha^2]^{-1} \quad (8.9)$$

the variance is independent of the value of  $y_1$  observed and  $\sigma_{\alpha_1|y_1}^2$  will be underestimated. This is incorrect behaviour since if  $y_1$  is an outlier it contains (almost) no information about the value of  $p(\alpha_1|y_1)$  so that  $p(\alpha_1|y_1)$  should be almost equal to  $p(\alpha_1)$ . The likelihood function based on 5a has the desired behaviour.

To calculate (8.6) it is necessary to maximize  $\phi(y_1, \alpha_1)$  with respect to  $\alpha_1$  and to calculate its hessian matrix with respect to  $\alpha_1$ .

For the maximization we employ the Newton-Raphson algorithm. Let  $\beta_0 = \mu_{\alpha_1}$

$$\beta_{i+1} = \beta_i - \{ D_{\alpha_1 \alpha_1}^2 \phi(y_1, \beta_i) \}^{-1} (D_{\alpha_1} \phi(y_1, \beta_i)) \quad (8.10)$$

This operation is carried out a fixed number  $r$  times and then  $\hat{\alpha}_1(y_1) \approx \beta_r$ . For “well behaved” problems the sequence  $\beta_i$  converges quadratically to  $\hat{\alpha}_1(y_1)$ . We approximate  $p(\alpha_1|y_1)$  by a multivariate normal with

$$\begin{aligned} \mu_{\alpha_1|y_1} &= \beta_r \\ \sigma_{\alpha_1|y_1}^2 &= \{ - D_{\alpha_1 \alpha_1}^2 \phi(y_1, \beta_r) \}^{-1} \end{aligned}$$



and approximate  $p(\alpha_2|y_1)$  by a multivariate normal with

$$\begin{aligned}\mu_{\alpha_2|y_1} &= T(\beta_r, y_1) \\ \sigma_{\alpha_2|y_1}^2 &= D_{\alpha_1} T_1(\beta_r, y_1) \sigma_{\alpha_1|y_1}^2 D_{\alpha_1} T_1(\beta_r, y_1)' + \sigma_\eta^2\end{aligned}$$

Now

$$p(y_2|y_1) = \int_{-\infty}^{\infty} p(y_2|\alpha_2)p(\alpha_2|y_1) d\alpha_2 \quad (8.11)$$

As above we maximize the integrand of (8.11) with respect to  $\alpha_2$  and use the Laplace approximation to the integral. This produces the sequence of conditional probabilities,  $p(y_i|y_{i-1})$ . The log-likelihood function for the observed sequence  $y_i$  is given by

$$\sum_{i=1}^n \log(p(y_i|y_{i-1})) \quad (8.12)$$

## Parameter estimation

Although we have not explicitly shown them the conditional likelihood functions  $p(y_i|y_{i-1})$  depend on a number of parameters. These parameters include the specification of  $T$ , other parameters in the probability density  $p(y_i|\alpha_i)$  and parameters which determine  $\sigma_\eta^2$ . If we denote these parameters by  $\theta$  and write  $(p(y_i|y_{i-1}, \theta))$  to indicate this dependence the log-likelihood function becomes

$$\sum_{i=1}^n \log(p(y_i|y_{i-1}, \theta)) \quad (8.13)$$

the maximum likelihood estimates for the parameter vector  $\theta$  are found by maximizing (8.13) with respect to  $\theta$ .

## The stochastic volatility model

The version of the stochastic volatility model presented here is from the paper Multivariate Stochastic Volatility Models: Estimation and a comparison with VGARCH Models by Danielsson.

It is assumed that  $y_i$  has a multivariate normal distribution with  $\mu_{y_i} = 0$  and covariance matrix  $\Omega_i(\alpha_i) = H_i(\alpha_i)R H_i(\alpha_i)$  where  $H_i(\alpha_i)$  is an  $m \times m$  diagonal matrix whose  $j$ 'th element on the diagonal is given by  $\exp(\alpha_{ij})/2$  where the  $\alpha_{ij}$  satisfy the relationship

$$\alpha_i = w + \text{elem\_prod}(\delta, \alpha_{i-1}) + \text{elem\_prod}(\lambda_1, y_{i-1}) + \text{elem\_prod}(\lambda_2, |y_{i-1}|) + \eta_i \quad (8.14)$$

where  $\eta_i$  is a multivariate normal random variable with  $\mu_{\eta_i} = 0$  and  $\sigma_{\eta_i}^2 = \sigma_{\eta}^2$ . If  $u$  and  $v$  are two vectors with  $j$ 'th component  $u_j$  and  $v_j$  `elem_prod(i, v)` is the vector with  $j$ 'th component  $u_j v_j$ .  $R$  is an  $m \times m$  positive definite matrix satisfying  $r_{jj} = 1$ , that is a correlation matrix. Then

$$\log(p(y_i|\alpha_i)) = -0.5 \log|\Omega_i(\alpha_i)| - 0.5 y_i' \Omega_i(\alpha_i)^{-1} y_i \quad (8.15)$$

and the distribution of  $\alpha_i|y_{i-1}$  is multivariate normal with mean vector and covariance matrix given by

$$\begin{aligned} \mu_{\alpha_i|y_{i-1}} &= w + \text{elem\_prod}(\delta, \mu_{\alpha_{i-1}|y_{i-1}}) + \text{elem\_prod}(\lambda, y_{i-1}) \\ \sigma_{\alpha_i|y_{i-1}}^2 &= i \text{ diag}(\delta) \sigma_{\alpha_{i-1}|y_{i-1}}^2 \text{diag}(\delta) + \sigma_{\eta}^2 \end{aligned} \quad (8.16)$$

$\text{diag}(\delta)$  is the diagonal matrix whose diagonal is equal to the vector  $\delta$ .

$$\begin{aligned} \log(p(y_i|\alpha_i)p(\alpha_i|y_{i-1})) &= -0.5 \log|\Omega_i(\alpha_i)| - 0.5 y_i' \Omega_i(\alpha_i)^{-1} y_i - 0.5 \log|\sigma_{\alpha_i|y_{i-1}}^2| \\ &\quad - 0.5 (\alpha_i - \mu_{\alpha_i|y_{i-1}})' (\sigma_{\alpha_i|y_{i-1}}^2)^{-1} (\alpha_i - \mu_{\alpha_i|y_{i-1}}) \end{aligned} \quad (8.17)$$

To perform the Newton-Raphson calculations it is necessary to calculate the first and second derivatives of expression (8.17) with respect to the parameter vector  $\alpha$ . This is the most involved part of the calculations and will depend on the particular form of the model. In the present case the calculations are simplified by the fact that  $\Omega_i$  only depends on  $\alpha$  through the diagonal matrix  $H(\alpha_i)$ .

The probability density function  $p(\alpha_1)$  is assumed to be multivariate normal with  $\mu_{\alpha_1} = \theta_0$  and  $\sigma_{\alpha_1}^2 = 0$ .

## The Data

The data consist of the daily Mark/Dollar and Yen/dollar exchange rates and the US and Japanese stock index data. There are 1301 time periods with some missing data. The missing data which are denoted by the impossibly large value of 10,000 were replaced with the average from the period before and after. They can however easily be estimated in the model is desired.

## The Results

The model was fit with various combinations of the parameters and the log-likelihood was examined to investigate the improvement in fit due to the addition of the parameters.

---

Parameters in model	number of parameters	log-likelihood
$w, \delta, R, \sigma_\eta^2$	24	3774.7
$w, \delta, R, \sigma_\eta^2, \lambda_1$	28	3806.6
$w, \delta, R, \sigma_\eta^2, \lambda_1, \theta_0$	32	3808.6
$w, \delta, R, \sigma_\eta^2, \lambda_1, \theta_0, \lambda_2$	36	3811.2

---

The parameters  $\theta_0$  and  $\lambda_2$  did not produce a significant improvement to the fit.  $\lambda_2$  measures the asymmetry in the response of the variance to positive and negative shocks.

Here are the parameter estimates and their standard deviations for the model with  $w, \delta, R, \sigma_\eta^2$ , and  $\lambda_1$ .

index	name	value	std dev
1	w(1)	-1.3749e-001	4.9434e-002
2	w(2)	-6.5649e-001	1.6161e-001
3	w(3)	3.1693e-002	1.0574e-002
4	w(4)	-1.2973e-002	1.5375e-002
5	lambda1(1)	1.5564e-001	4.9688e-002
6	lambda1(2)	1.8647e-001	6.9525e-002
7	lambda1(3)	-6.9265e-002	1.4158e-002
8	lambda1(4)	-1.6689e-001	3.1626e-002
9	delta(1)	8.2229e-001	4.6074e-002
10	delta(1)	5.0848e-001	1.0785e-001
11	delta(1)	9.5763e-001	1.4602e-002
12	delta(1)	9.3610e-001	1.8812e-002
29	R(1,1)	1.0000e+000	0.0000e+000
30	R(1,2)	5.3821e-001	2.2883e-002
31	R(1,3)	-7.1704e-002	2.9477e-002
32	R(1,4)	-3.8796e-002	2.9278e-002
33	R(2,1)	5.3821e-001	2.2883e-002
34	R(2,2)	1.0000e+000	0.0000e+000
35	R(2,3)	-1.2932e-001	2.9111e-002
36	R(2,3)	-4.1466e-002	2.9468e-002
37	R(3,1)	-7.1704e-002	2.9477e-002
38	R(3,2)	-1.2932e-001	2.9111e-002
39	R(3,3)	1.0000e+000	0.0000e+000
40	R(1,4)	8.8811e-002	2.9085e-002
41	R(4,1)	-3.8796e-002	2.9278e-002
42	R(4,2)	-4.1466e-002	2.9468e-002
43	R(4,3)	8.8811e-002	2.9085e-002
44	R(4,4)	1.0000e+000	0.0000e+000
45	Omega(1,1)	6.5973e-001	6.3099e-002
46	Omega(1,2)	1.9827e-001	1.6129e-002
47	Omega(1,3)	-1.3395e-001	5.4982e-002
48	Omega(1,4)	-3.5161e-002	2.6676e-002
49	Omega(2,1)	1.9827e-001	1.6129e-002
50	Omega(2,2)	2.0570e-001	2.3994e-002
51	Omega(2,3)	-1.3489e-001	3.2608e-002
52	Omega(2,4)	-2.0985e-002	1.5016e-002
53	Omega(3,1)	-1.3395e-001	5.4982e-002
54	Omega(3,2)	-1.3489e-001	3.2608e-002
55	Omega(3,3)	5.2895e+000	5.7872e-001

```

56  Omega(3,4)  2.2791e-001  7.9318e-002
57  Omega(4,1) -3.5161e-002  2.6676e-002
58  Omega(4,2) -2.0985e-002  1.5016e-002
59  Omega(4,3)  2.2791e-001  7.9318e-002
60  Omega(4,4)  1.2451e+000  1.7043e-001
61  Z(1,1)     2.3967e-001  7.4268e-002
62  Z(1,2)     2.0711e-001  5.5599e-002
63  Z(1,3)     3.8832e-002  1.8505e-002
64  Z(1,4)     2.4097e-002  2.0344e-002
65  Z(2,1)     2.0711e-001  5.5599e-002
66  Z(2,2)     4.6309e-001  1.1143e-001
67  Z(2,3)     3.4298e-002  2.3017e-002
68  Z(2,4)     9.6831e-003  2.9999e-002
69  Z(3,1)     3.8832e-002  1.8505e-002
70  Z(3,2)     3.4298e-002  2.3017e-002
71  Z(3,3)     3.9101e-002  1.6885e-002
72  Z(3,4)     2.4602e-002  1.1053e-002
73  Z(4,1)     2.4097e-002  2.0344e-002
74  Z(4,2)     9.6831e-003  2.9999e-002
75  Z(4,3)     2.4602e-002  1.1053e-002
76  Z(4,4)     9.6109e-002  3.4268e-002

```

The AD Model Builder TPL file for the model is given below.

```

DATA_SECTION
  init_int ndim
  init_int nobs
  int ndim1
  int ndim2
  !! ndim1=ndim*(ndim+1)/2;
  !! ndim2=ndim*(ndim-1)/2;
  init_matrix Y(1,nobs,1,ndim)
LOC_CALCS
  // replace missing values (10000) with the average of before and after.
  for (int i=2;i<nobs;i++)
    for (int j=1;j<=ndim;j++)
      if (Y(i,j)==10000)
        {
          int i2=i+1;
          do
            {
              if (Y(i2,j)==10000)
                i2++;
              else
                break;
            }
          while(1);
          Y(i,j)=(Y(i-1,j)+Y(i2,j))/2.;
          if (Y(i,j)>100.0) // did this work
            cerr << " Y(i,j) too big " << Y(i,j) << endl;
        }
  }
END_CALCS

PARAMETER_SECTION
  matrix h_mean(1,nobs,1,ndim)
  3darray h_var(1,nobs,1,ndim,1,ndim)
  number ldR;
  init_vector theta0(1,ndim,3);
  vector lmin(1,nobs)

```

```

init_bounded_vector w(1,ndim,-10,10)
vector w1(1,ndim)
init_vector lambda(1,ndim,2)
init_vector lambda2(1,ndim,-1)
init_bounded_vector delta(1,ndim,0,.98)
sdreport_matrix R(1,ndim,1,ndim)
sdreport_matrix Omega(1,ndim,1,ndim)
matrix ch_R(1,ndim,1,ndim)
matrix Rinv(1,ndim,1,ndim)
init_bounded_vector v_R(1,ndim2,-1.0,1.0)
sdreport_matrix Z(1,ndim,1,ndim)
matrix ch_Z(1,ndim,1,ndim)
init_bounded_vector v_Z(1,ndim1,-1.0,1.0)
matrix S(1,ndim,1,ndim);
objective_function_value f
INITIALIZATION_SECTION
    delta 0.9
PROCEDURE_SECTION

fill_the_matrices();
int sgn;
ldR=ln_det(R,sgn);
Rinv=inv(R);
dvar_vector tmp(1,ndim);
dvar_matrix sh(1,ndim,1,ndim);
h_mean(1)=theta0;
h_var(1)=0;
for (int i=2;i<=nobs;i++)
{
    dvar_vector tmean=update_the_means(w,h_mean(i-1),Y(i-1));
    dvar_matrix v=update_the_variances(h_var(i-1));
    tmp=tmean;
    dvar_vector h(1,ndim);
    dvar_vector gr(1,ndim);
    for (int ii=1;ii<=4;ii++) // do the Newton-Raphson 4 times
    {
        xfp12(tmp, Y(i),tmean,v,gr,sh); // get 1st and 2nd derivatives
        h=-solve(sh,gr); //sh is hessian and gr is the gradient
        tmp+=h; // add new step h
    }
    double nh=norm2(value(h)); // check size of h for convergence
    if (nh>1.e-1)
        cout << "No convergence in NR " << nh << endl;
    if (nh>1.e+02)
    {
        f+=1.e+7; // this ensures that the function minimizer will take a
        return; // smaller step
    }
    h_mean(i)=tmp;
    h_var(i)=inv(sh);
    lmin(i)=fp(tmp,Y(i),tmean,v);
    int sgn;
    f+=lmin(i)+0.5*ln_det(sh,sgn); // Laplace approximation
}
f-=0.5*nobs*ndim*log(2.*3.14159);
Omega=S;

FUNCTION dvar_vector update_the_means(dvar_vector& w,dvar_vector& m,dvector& e)

```

```

dvar_vector tmp= w+elem_prod(delta,m)+elem_prod(lambda,e);
if (active(lambda2))
    tmp+=elem_prod(lambda2,fabs(e));
return tmp;

FUNCTION dvar_matrix update_the_variances(dvar_matrix& v)
dvar_matrix tmp(1,ndim,1,ndim);
for (int i=1;i<=ndim;i++)
{
    for (int j=1;j<=i;j++)
    {
        tmp(i,j)=delta(i)*delta(j)*v(i,j);
        if (i!=j) tmp(j,i)=tmp(i,j);
    }
}
tmp+=Z;
return tmp;

FUNCTION dvariable fp(dvar_vector& h, dvector& y, dvar_vector& m,dvar_matrix& v)
dvar_vector eh=exp(.5*h);
for (int i=1;i<=ndim;i++)
{
    for (int j=1;j<=i;j++)
    {
        S(i,j)= eh(i)*eh(j)*R(i,j);
        if (i!=j) S(j,i)=S(i,j);
    }
}

dvariable lndet;
dvariable sgn;
dvar_vector u=solve(S,y,lndet,sgn);
dvariable l;
l=.5*lndet+.5*(y*u);
dvar_vector hm=h-m;
w1=solve(v,hm,lndet,sgn);
l+=.5*lndet+.5*(w1*hm);
return l;

FUNCTION void xfp12(dvar_vector& h, dvector& y,dvar_vector& m,dvar_matrix& v, dvar_vector
gr,dvar_matrix& hess)
dvar_vector ehinv=exp(-.5*h);
dvariable lndet;
dvariable sgn;
dvar_vector ys=elem_prod(ehinv,y);
dvar_vector u=Rinv*ys;
gr=0.5;
dvar_vector vv=elem_prod(ys,u);
gr-=.5*vv;
dvar_vector hm=h-m;
dvar_vector w=solve(v,hm,lndet,sgn);
gr+=w;
for (int i=1;i<=ndim;i++)
{
    for (int j=1;j<=i;j++)
    {
        hess(i,j)=0.25*ys(i)*ys(j)*Rinv(i,j);
        if (i!=j) hess(j,i)=hess(i,j);
    }
}

```

```

    }
}
for (i=1;i<=ndim;i++)
{
    hess(i,i)+=.25*vv(i);
}
hess+=inv(v);

FUNCTION fill_the_matrices
int ii=1;
ch_Z.initialize();
for (int i=1;i<=ndim;i++)
{
    for (int j=1;j<=i;j++)
        ch_Z(i,j)=v_Z(ii++);
    ch_Z(i,i)+=0.5;
}
Z=ch_Z*trans(ch_Z);
ch_R.initialize();
ii=1;
for (i=1;i<=ndim;i++)
{
    for (int j=1;j<i;j++)
        ch_R(i,j)=v_R(ii++);
    ch_R(i,i)+=0.1;
    ch_R(i)/=norm(ch_R(i));
}
R=ch_R*trans(ch_R);

REPORT_SECTION
report<<"observed"<<Y<<endl;
for (int i=1;i<=nobs;i++)
{
    report<< "mean" <<endl;
    report<< h_mean(i) <<endl;
    report<< "covariance" <<endl;
    report<<h_var(i)<<endl;
    report<<endl;
}
report<< "S(nobs) " << endl;
report<< Omega << endl;
report<< "Z " << endl;
report<< Z << endl;
report<< "R " << endl;
report<< R << endl;

TOP_OF_MAIN_SECTION
arrmblsize=20000000;
gradient_structure::set_CMPDIF_BUFFER_SIZE(25000000);
gradient_structure::set_GRADSTACK_BUFFER_SIZE(1000000);

```





## Chapter 9

# Using Vectors of initial parameter types

This chapter introduces three new AD Model Builder types. They are the `init_number_vector`, `init_vector_vector`, `init_matrix_vector`, and the bounded versions of these, the `init_bounded_number_vector`, `init_bounded_vector_vector`, and `init_bounded_matrix_vector`. To understand the usefulness of these objects consider an application which has two `init_number` objects.

```
PARAMETER_SECTION
  init_bounded_number a1(0.2,1.0,1)
  init_bounded_number a2(-1.0,0.3,2)
```

This creates two bounded numbers with different upper and lower bounds and becoming active in different phases of the minimization. Now however suppose that the number of numbers we wish to have in the model depends on some integer read in at run time such as

```
DATA_SECTION
  init_int n
  // ...

PARAMETER_SECTION
  // want to have n numbers
  init_bounded_number a1(0.2,1.0,1)
  init_bounded_number a2(-1.0,0.3,2)
  // ....
  init_bounded_number an(-4.0,-3.0,n)
```

the above code is a sketch of what we want to achieve. It can not be accomplished with that kind of coding of course because at compile time we don't have the value for `n`, and in any event if `n` is large this sort of coding is boring. Dynamic arrays are the answer to this problem. One could try the following

```
DATA_SECTION
  init_int n
  // ...
```

```

PARAMETER_SECTION
// want to have n numbers
init_bounded_vector a(1,n,-1.0,1.0,1)

```

but this won't work because for an `init_bounded_vector` the bounds and the starting phase are the same for all components of the vector. The `init_bounded_number_vector` class is intended to solve this problem.

```

DATA_SECTION
  init_int n
  // ...

PARAMETER_SECTION
  // need to create some vectors to hold the bounds and
  // phase numbers
LOC_CALCS
  dvector lb(1,n);
  dvector ub(1,n);
  ivector ph(1,n);
  // get the desired values into lb,ub,ph somehow
  lb.fill_seqadd(1,0.5);
  ub.fill_seqadd(2,0.5);
  ph.fill_seqadd(1,1);
END_CALCS
  init_bounded_number_vector a(1,n,lb,ub,ph)

```

Then `a(1)` is an object of type `init_bounded_number` with bounds `lb(1)` and `ub(1)` and becoming active in phase `ph(1)`. Any of these three fields can be replaced with a number or integer if the bound or phase number is constant such as

```

init_bounded_number_vector a(1,n,1.0,ub,2)

```

where the lower bound is 1.0 and the phase number is 2.

## Chapter 10

# Creating Dynamic Link Libraries with AD Model Builder

For performance reasons many nonlinear modeling routines for packages such as Splus or Gauss or spreadsheets such as Excel are written in other languages such as C or FORTRAN and compiled as DLL's or shared libraries. Due to AD Model builder's support for nonlinear statistical modeling, it is generally much faster and easier to produce the code for a nonlinear statistical model with ADMB rather than C or FORTRAN. This code can then be put into a shared library (DLL) and called from Splus as though it were a part of the language.

This section focuses on creating DLL's for Splus version 4 release 3 under Windows 95/NT, or for the R programming environment under Windows 95/NT or Linux. The construction can be easily modified to produce DLL's which can be used by other programs such as Visual Basic or spreadsheets like Excel.

There are two example programs, a very simple example to illustrate the ideas, and a program to estimate the parameters from a mixture of two bivariate normal distributions.

We begin with the simple example. We wish to minimize the function  $f$  given by

$$f = (x_1 - 1.0)^2 + \sum_{i=1}^{n-1} (x_{i+1} - x_i)^2$$

with respect to the  $n$  dimensional vector  $x$ . The starting values are  $x = (0, 0, \dots, 0)$ .

While this is a quadratic function which can be solved by special methods we do not use this special structure because we want to illustrate the technique on general nonlinear models.

There are three modifications to a stand alone AD Model Builder program which must be made to produce a DLL.

1. The command line option `-dll` is given to the `tp12cpp` program which translates the template file into a C++ file.

2. The user must decide which data and parameter objects are to be passed to or returned from the DLL and the TPL file modified accordingly.
3. The interface code must be written in the calling language.

objects are to be passed to or returned from the DLL.

Objects which are to be passed into or returned from the DLL are identified by putting the prefix `dll_` before their declarations.

In this example the number of independent variables is passed from the calling program to the DLL. Thus the `init_int nvar` is modified to `dll_init_int nvar`. The calling program expects to get the minimum value `freturn` and the minimizing values of the `init_vector` `x` returned to it so they are declared to be of type `dll_number` and `dll_init_vector`.

```
DATA_SECTION
  dll_int nvar
PARAMETER_SECTION
  dll_init_vector x(1,nvar)
  dll_number freturn
  objective_function_value f
PROCEDURE_SECTION
  f=square(x(1)-1.0);
  for (int i=1;i<nvar;i++)
  {
    f+=square(x(i+1)-x(i));
  }
  freturn=f;
```

## Compiling the code to produce a DLL

The exact form of the commands used to produce a DLL or shared library depend on the compiler used and the operating system.

assuming that the template file is named `xxxx.tpl` for NT/9? using the `gcc2.95-mingw32` compiler the commands are:

```
tpl2cpp -dll %1

c++ -fpermissive -O3 -c -DBUILDING_DLL=1 -D__GNUDOS__ -I. i
  -If:/admodel/include -o %1.o %1.cpp

dllwrap -def %1.def --implib lib%1.a --driver-name c++ -o %1.dll %1.o
  -Lf:/admodel/lib -ladmod -ladt -lado -lm
```

where the symbol be replaced by `$1` in Linux) should be replaced by `xxxx`

Of course you don't want to type all this every time so the commands should be replaced in a bat file such as `makedll.bat`. Then to compile the TPL into a DLL it is only necessary to type

```
makeadll xxxx
```

where `xxxx.tpl` is the template file. For debugging purposes you may find that you want to edit the `cpp` file so you will not want to run `tpl2cpp` every time. In that case the first line should be removed from the bat file.

To call the DLL from SPLUS the `dll.load` function is used to load the library.

```
dll.load("simpdll.dll",symbol="simpdll")
n<-100
x<-rep(0,n)
freturn<-0
ans<-C("simpdll",as.integer(n),x = as.double(x),as.double(f)," -sp -crit 1.e-8 -nohess")
```

The final parameter " `-sp -crit 1.e-8 -nohess`" is a string which serves the same function as command line options in AD Model Builder programs. the `-sp` option tells the DLL that it is being run from SPLUS so that it can print into the Splus command window. The `-crit` option sets the convergence criterion for the magnitude of the components of the gradient and the `-nohess` option suppresses the calculation of the hessian at the minimum. It must be present although it can be blank.

It is necessary that SPLUS can find the DLL. If there is trouble a full path name can be used as in

```
dll.load("c://mydlls//simpdll.dll",symbol="simpdll")
```

## The splus objects

At present the objects which can be put in the TPL file for communication with Splus in the data section are

```
dll_init_int
dll_iinit_number
dll_iinit_vector
dll_init_matrix
dll_int
dll_number
dll_vector
dll_matrix
```

while in the `PARAMETER_SECTION` they are

```
dll_init_number
dll_init_bounded_number
dll_init_vector
dll_init_bounded_vector
dll_init_matrix
dll_number
dll_vector
dll_matrix
```

These objects act the same as the corresponding AD Model Builder objects without the `dll_` prefix. For initial parameters the difference is that they are assumed to get their initial values from Splus.

Note that by default Splus stores elements of a Matrix by columns, that is contiguous areas of memory run down columns. AD Model Builder stores its elements by rows so that when a matrix objects passed to it from Splus it expects the object to be stored by column and does a transpose operation on it. At the conclusion of the AD Model Builder program the object is passed back to Splus via the inverse operation. This process should be transparent to the user.

## Debugging the DLL's

Before you compile your program as a DLL it is easiest if you first compile it as a stand alone application and debug it. then you can simply put the `dll_` prefix before those objects which you wish to have passed to and from the calling program. Also is inconvenient to debug the DLL's from Splus directly. Errors in the code usually cause Splus to crash. Also printing results to the screen from a DLL can be problematic if the calling program does not provide for it. To alleviate this problem it is possible to call the function in the DLL from a C or C++ routine. This enables the use of symbolic debuggers etc. to debug the code and enables screen IO. Here is C code which can load the DLL and call the function.

```
#include <stdio.h>
#include <windows.h>

typedef __declspec(dllexport) void _export (*MYPROC)(int *_nvar,double *_x,double
*_freturn,char ** sp_options);

VOID main(int argc,char * argv[])
{
    HINSTANCE h;
    MYPROC p;
    /* Now invent the objects we need to pass to the DLL */
    int nvar=50;
    double x[50];
    double freturn;
    char * str;
    int i;
    char * str = " -nox -crit 1.e-7 ";
    h=LoadLibrary("simpdll"); /* load the DLL */
    if (h)
    {
        printf("loaded simpdll.dll successfully\n");
        /* get pointer to the function */
        p=(MYPROC) GetProcAddress(h,"_simpdll");
        if (p)
        {
            freturn=0.0;
            for (i=0;i<nvar;i++)
                x[i]=0.0;
        }
    }
}
```

```

    p(&nvar,x,&freturn,&str);

    printf("function value = %lf\n",&freturn);
    for (i=0;i<nvar;i++)
        printf("x[%d]= %lf\n",i,x[i]);

    }
    else
        printf("Can't find function simdll in DLL\n");
}
else
    printf("Can't load simdll.dll\n");
}

```

This code can be compiled with the command

```
gcc -otestsim.exe testsim.c
```

which will produce the program `testsim.exe`. running this program will load the DLL, find the function in it and call it. at the end it will report the results obtained.

## Understanding what is being passed to the DLL

The most difficult part of calling a C++ DLL from some other type of application is understanding what the correct formalism for passing different objects between the two. passing the various objects. for example a string in Visual Basic may be a very different object from the simple `char *` (pointer to char) of the C and C++ languages. If you get it wrong then the program will usually crash when the code in the DLL tries to access the object. The simplest way to debug this is to have the DLL code simply print out the values of the passed objects. (However keep in mind that simply trying to access the values for printing may cause the program to crash).

Consider the CPP for the example TPL code given above.

```

#include <admodel.h>

#include <simpdll.h>

model_data::model_data(splus_args& ad_spa)
{
    nvar.allocate(ad_spa.nvar,"nvar");
}

model_parameters::model_parameters(int sz,int argc,char * argv[], splus_args& ad_spa) :
    ad_comm(argc,argv), model_data(ad_spa) , function_minimizer(sz)
{
    initializationfunction();
    x.allocate(ad_spa.x,1,nvar,"x");
    freturn.allocate(ad_spa.freturn,"freturn");
    f.allocate("f");
}

```

```

void model_parameters::userfunction(void)
{
    f=square(x(1)-1.0);
    for (int i=1;i<nvar;i++)
    {
        f+=square(x(i+1)-x(i));
    }
    freturn=f;
}

void model_parameters::preliminary_calculations(void){}

model_data:: model_data()
{}

model_parameters:: model_parameters()
{}

void model_parameters::report(void){}

void model_parameters::final_calcs(void){}

void model_parameters::set_runtime(void){}

#ifdef _BORLANDC_
    extern unsigned _stklen=10000U;
#endif

#ifdef __ZTC__
    extern unsigned int _stack=10000U;
#endif

    long int arrmblsize=0;
extern "C" {

#ifdef !defined(__delcspec)
# define __declspec(x)
#endif

#ifdef !defined(__BORLANDC__)
# define _export
#endif

__declspec(dllexport) void _export simpdll(int *_nvar,double *_x,double *_freturn,char **
sp_options)
{
    int argc=1;
    try {
        char **argv=parse_sp_options("simpdll",argc,*sp_options);
        do_dll_housekeeping(argc,argv);
        splus_args ad_spa(_nvar,_x,_freturn);
        gradient_structure::set_NO_DERIVATIVES();
        gradient_structure::set_YES_SAVE_VARIABLES_VALUES();
        #if defined(__GNUDOS__) || defined(DOS386) || defined(__DPMI32__) ||
defined(__MSVC32__)
            if (!arrmblsize) arrmblsize=150000;
        #else
        #endif
    }
}

```



```

        if (!arrmblsize) arrmblsize=25000;
    #endif
    model_parameters mp(arrmblsize,argc,argv,ad_spa);
    mp.iprint=10;
    mp.preliminary_calculations();
    mp.computations(argc,argv);
    cleanup_argv(argc,&argv);
    ad_make_code_reentrant();
}
catch (spdll_exception spe){
    if (ad_printf && spe.e) (*ad_printf) ("abnormal exit from newtest\n");
}
}
}

```

For now we are only interested in the part of the code after the beginning of the function

```

__declspec(dllexport) void _export simpdll(int *_nvar,double *_x,double *_freturn,char **
sp_options)
{
    int argc=1;
    try {
        .....

```

Modify this code to:

```

__declspec(dllexport) void _export simpdll(int *_nvar,double *_x,double *_freturn,char **
sp_options)
{
    cout << " nvar = " << *_nvar << endl;
    return;
    int argc=1;
    try {
        .....

```

If everything is OK this will simply print out the value of `nvar` and return to the calling program. Then the value of `x` can be printed out as well with code like

```

__declspec(dllexport) void _export simpdll(int *_nvar,double *_x,double *_freturn,char **
sp_options)
{
    cout << " nvar = " << *_nvar << endl;
    cout << " x = " << endl;
    for (int i=0;i<*_nvar;i++)
        cout << _x[i] << endl;
    cout << " freturn = " << *_freturn << endl;
    cout << " sp_options = " << *sp_options << endl;
    return;
    int argc=1;
    try {
        .....

```

If you don't have access to the screen the above code can be modified to print to a file.

```

__declspec(dllexport) void _export simpdll(int *_nvar,double *_x,double *_freturn,char **
sp_options)
{
    ofstream ofs("logfile");

```

```

ofs << " nvar = " << *_nvar << endl;
ofs << " x = " << endl;
for (int i=0;i<*_nvar;i++)
    ofs << _x[i] << endl;
ofs << " freturn = " << *_freturn << endl;
ofs << " sp_options = " << *sp_options << endl;
return;
int argc=1;
try {
    .....

```

After running the program you should find the values of the objects printed into a file named logfile.

Splus passes objects to the DLL by address, that is it finds the address in memory of the object and passes that value. So the integer nvar is not passed itself but the address. In C or C++ you take the address of an object with the & operator. a given the address of an object you access the object with the \* operator. In the above code `_nvar` is the address of an integer passed by the calling program to the DLL and `*_nvar` accesses the object. So the line of code

```
*_nvar=5;
```

will set the values of the integer to 5 back in the calling program. when Splus passes a vector object it passes the address of the first element in the vector. So if the vector is a vector of double precision numbers (an object of type `double` in C) it will pass a pointer to `double`. So in the above code `_x` is the address of the first element of the vector and `*_x` is the first element so that

```
*_x=12.55;
```

will set the first element in the vector equal to 12.55. To access other elements of the vector use the [] operators.

```

x[0]=12.55; // same as *_x=12.55
x[4]=-2.5; // sets the 5 element equal to -2.5

```

## Passing strings from Splus to a DLL

A string in C is a pointer to an array of elements of type `char`. It might be logical to conclude that Splus would pass the address of the first elementa of the array. This is not the case – Splus passes the address of the object pointing to the first element of the array (a `char **` in C). So in the above code if you want to print the second element of the string point to by `sp_options` to the standard output device you would use the code

```
cout << (*sp_options)[1] << endl; // print the second element of the string
```

You must use the parentheses because the [] operation has higher precedence than the \* operation.

## A mixture of two bivariate normal distributions

This is a more complicated example. Let  $x_i$  be a collection of two dimensional vectors drawn at random from a mixture of two bivariate normal distributions with means  $\mu_i$  and covariance matrices  $\Sigma_i$ . The data to be analyzed are shown here. They consist of 500 point from the mixture with 25component. Both samples have positively corellated components so that they both lie near the line  $y=x$ . this makes them difficult to separate. The means used for the simulations were

(0,0)      (1,0)

while the covariance matrices used for the simulation were.

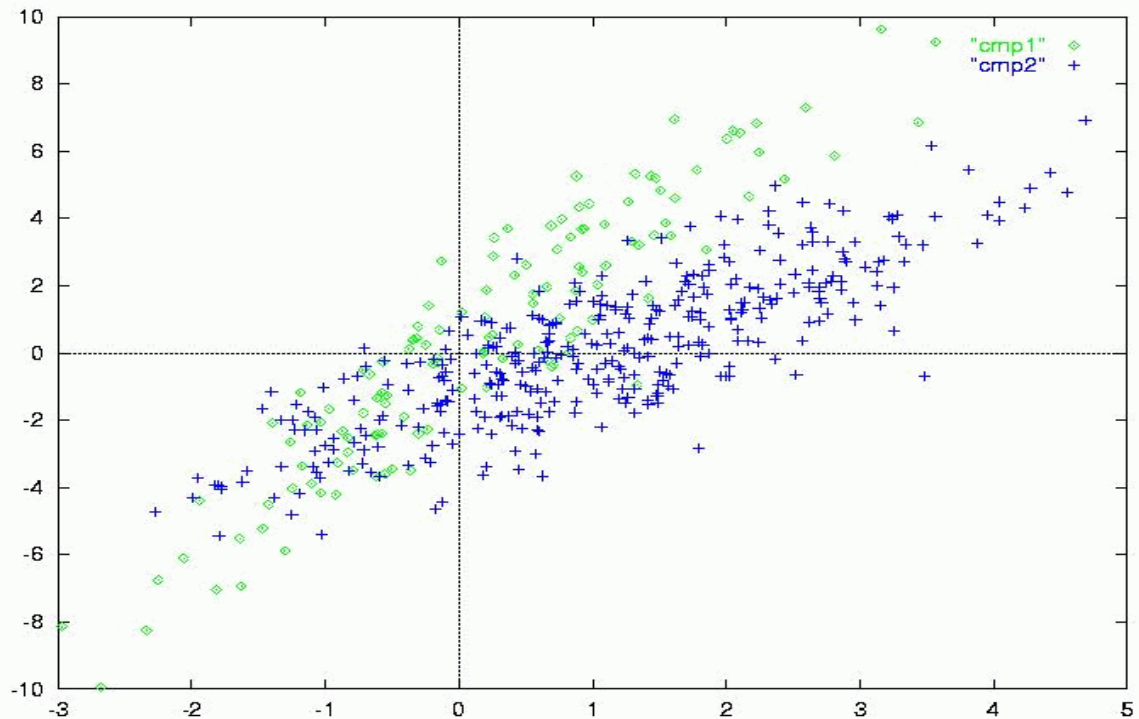
1.77778 4.74074      1.77778 2.37037  
4.74074 14.4198      2.37037 4.93827

The estimates for these parameters obtained by the model were

(0.026,0.059)      (1.266,0.287)  
1.42409 3.86336      1.66321 2.34985  
3.86336 12.2286      2.34985 4.94363

The estimated proportions were

0.343    0.657



The minimization is carried out in three phases. For the first phase only the proportions of the mixture are estimated, with the parameters which determine the covariance matrices and the means held fixed. For the second phase the covariance matrices are estimated as well, with the means held fixed. For the third and final phase all the parameters are estimated. The idea is that the user should start with some good estimates for the means. Of course the model could be run several times with different initial estimates and if different solutions are obtained then the one with the best fit would be chosen.

The initial values used for the means and standard deviations were

$$\begin{pmatrix} -1,0 & (2,0) \\ \begin{matrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \end{matrix} \end{pmatrix}$$

The initial values used for the proportions were

$$\begin{pmatrix} 0.5 & 0.5 \end{pmatrix}$$

The log-likelihood function for the sample is

$$\sum_{i=1}^n \log \left\{ \begin{aligned} & p_1 |\Sigma_1|^{-1/2} \exp(-0.5(x_i - \mu_1)' \Sigma_1^{-1}(x_i - \mu_1)) \\ & + p_2 |\Sigma_2|^{-1/2} \exp(-0.5(x_i - \mu_2)' \Sigma_2^{-1}(x_i - \mu_2)) \end{aligned} \right\} \quad (10.1)$$

The main technical difficulty in maximizing the log-likelihood function is parameterizing the covariance matrices in such a way that they will be positive definite. This is done by employing a "positivized" Choleski decomposition.  $\Sigma_i$  as  $\Sigma_i = C_i C_i' + \lambda I$  where  $C_i$  is a lower triangular matrix,  $\lambda > 0$  is a "small" positive number and  $I$  is the identity matrix. The proportions in the mixture are parameterized by a bounded vector of parameters which is normalized so that the components will sum to 1. The code for the example follows.

```

tmp1.initialize();
tmp2.initialize();
int ii=1;
int i=0;
for (i=1;i<=2;i++) { // fill lower triangle
  for (int j=1;j<=i;j++) {
    tmp1(i,j)=C1(ii);
    tmp2(i,j)=C2(ii);
    ii++;
  }
}
S1=tmp1*trans(tmp1); // form S1 S2 from Choleski decomp.
S2=tmp2*trans(tmp2);
for (i=1;i<=2;i++) { // to make positive definite
  S1(i,i)+=0.1;
  S2(i,i)+=0.1;
}
dvariable det1=sqrt(det(S1));
dvariable det2=sqrt(det(S2));
dvar_matrix S1inv=inv(S1);
dvar_matrix S2inv=inv(S2);
for (i=1;i<=nobs;i++) // add up minus log-likelihood
{
  // add the 1.e-10 to avoid log(0) and for robustness
  f-= log(1.e-10+p(1)/det1*exp(-.5*(obs(i)-mu1)*S1inv*(obs(i)-mu1))
    +p(2)/det2*exp(-.5*(obs(i)-mu2)*S2inv*(obs(i)-mu2)));
}
RUNTIME_SECTION
  maximum_function_evaluations 50,100,10000
REPORT_SECTION
  report << "First mean = " << endl << mu1 << endl;
  report << "First covariance matrix = " << endl<< S1 << endl;
  report << "Second mean = " << endl << mu2 << endl;
  report << "Second covariance matrix = " << endl << S2 << endl;

```

This example can be run by using the following Splus source code.

```

nobs<-scan("bimix.dat",n=1)
x<-matrix(scan("bimix.dat",skip=1),nrow=nobs,ncol=2,byrow=TRUE)
pcoff<-rep(.5,2)
C1<-rep(1,3)
C2<-rep(1,3)
C1[2]<-0
C2[2]<-0
p<-rep(0,2)
mu1<-rep(0,2)
mu1[1]<--1
mu2<-rep(0,2)
mu2[1]<-2
S1<-matrix(0,nrow=2,ncol=2)
S2<-matrix(0,nrow=2,ncol=2)
dll.load("bimix.dll",symbol="bimix")
ans<- .C("bimix",nobs=as.integer(nobs),as.double(x),pcoff=as.double(pcoff),
  C1=as.double(C1),C2=as.double(C2),mu1=as.double(mu1),mu2=as.double(mu2),
  S1=as.double(S1),S2=as.double(S2),p=as.double(p)," -sp -nohess ")
dll.unload("bimix.dll")
S1<-matrix(ans$S1,nrow=2)
S2<-matrix(ans$S2,nrow=2)
mu1<-ans$mu1

```

```

mu2<-ans$mu2
p<-ans$p
print ("Estimated proportions")
print(p)
print ("Estimated mean for component 1")
print(mu1)
print ("Estimated mean for component 2")
print(mu2)
print ("Estimated covariance matrix for component 1")
print(S1)
print ("Estimated covariance matrix for component 2")
print(S2)

```

This code only works under NT/95 for version 4 release 3. Assuming that you have put the code where Splus can find it you can run the example from Splus by typing

```
source("bimix.spl")
```

There is also a file, bimix.r, which will run the program under R. However at present for Windows the R version will not print out any intermediate results so be patient and the final estimates will appear when the minimization has converged. After the program executes the parameter estimates can be found in the Splus variables p, mu1, mu2, S1, and S2.

## Interpretation of the parameter estimates

If the user desires, (remove the -nohess option) the program computes estimates of the variances of the parameter estimates.

index	name	value	std dev
1	pcoff	3.5511e-01	1.5693e+00
2	pcoff	6.7911e-01	2.9777e+00
3	C1	1.1507e+00	7.9990e-02
4	C1	3.3574e+00	2.8240e-01
5	C1	9.2537e-01	1.7504e-01
6	C2	1.2503e+00	7.7426e-02
7	C2	1.8795e+00	1.2641e-01
8	C2	1.1451e+00	8.3415e-02
9	mu	2.6366e-02	1.2791e-01
10	mu	5.9418e-02	3.4832e-01
11	mu	1.2627e+00	1.4717e-01
12	mu	2.8665e-01	1.7818e-01
13	p	3.4336e-01	6.7238e-02
14	p	6.5664e-01	6.7238e-02

The program also reports the correlation matrix

index	name	value	std dev	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	pcoff	3.551e-01	1.569e+00	1.000													
2	pcoff	6.791e-01	2.977e+00	0.997	1.000												
3	C1	1.150e+00	7.999e-02	-0.039	-0.021	1.000											
4	C1	3.357e+00	2.824e-01	-0.094	-0.052	0.736	1.000										
5	C1	9.253e-01	1.750e-01	0.067	0.036	0.031	-0.394	1.000									
6	C2	1.250e+00	7.742e-02	-0.071	-0.039	0.156	0.266	-0.070	1.000								

7	C2	1.879e+00	1.264e-01	-0.016	-0.009	-0.066	-0.046	-0.087	0.613	1.000										
8	C2	1.145e+00	8.341e-02	-0.072	-0.039	0.031	0.343	-0.308	0.138	-0.116	1.000									
9	mu	2.636e-02	1.279e-01	-0.000	-0.000	0.147	-0.054	0.285	0.349	0.163	-0.212	1.000								
10	mu	5.941e-02	3.483e-01	-0.045	-0.024	0.198	0.160	-0.012	0.411	0.245	-0.066	0.861	1.000							
11	mu	1.262e+00	1.471e-01	0.115	0.063	-0.295	-0.521	0.257	-0.572	-0.170	-0.322	-0.225	-0.421	1.000						
12	mu	2.866e-01	1.781e-01	0.063	0.034	-0.237	-0.247	0.071	-0.482	-0.265	0.003	-0.363	-0.460	0.803	1.000					
13	p	3.433e-01	6.723e-02	0.148	0.081	-0.266	-0.636	0.450	-0.482	-0.111	-0.487	-0.001	-0.302	0.773	0.426	1.000				
14	p	6.566e-01	6.723e-02	-0.148	-0.081	0.266	0.636	-0.450	0.482	0.111	0.487	0.001	0.302	-0.773	-0.426	-1.000	1.000			





# Chapter 11

## Command line options

AD Model Builder has a number of options which can be invoked at the command line. A list of current options can be displayed by typing the name of the application followed by `-?`. You will see a display like:

```
AD Model Builder version 4.5.0 copyright (c) 1993 1998 Otter Research Ltd
USAGE--kalman options
where an option consists of -option_tag followed by arguments if necessary
-ainp NAME      change default ascii input parameter file name to NAME
-binp NAME      change default binary input parameter file name to NAME
-est           only do the parameter estimation
-ind NAME       change default input data file name to NAME
-lmn N         use limited memory quasi newton -- keep N steps
-lprof         perform profile likelihood calculations
-prsave        save the independent variables from the profile calculations
-maxph N       increase the maximum phase number to N
-mcdiag        use diagonal covariance matrix for mcmc with diagonal values 1
-mcmc [N]      perform markov chain monte carlo with N simulations
-mcmult N      multiplier N for mcmc default
-mcr           resume previous mcmc
-mcnoscale     don't rescale step size for mcmc depending on acceptance rate
-mcgrope N     use probing strategy for mcmc with factor N
-mcseed N      seed for random number generator for markov chain monte carlo
-mccale N      rescale step size for first N evaluations
-mcsave N      save the parameters for every N'th simulation
-mceval        Go through the saved mcmc values from a previous mcsave
-mcpin NAME    Read the starting values for MCMC from the file NAME
-crit N        set gradient magnitude convergence criterion to N
-iprint N      print out function minimizer report every N iterations
-maxfn N       set maximum number of function eval's to N
-rs           if function minimizer can't make progress rescale and try again
-nox          don't show vector and gradient values in function minimizer screen report
-phase N      start minimization in phase N
-simplex       use simplex algorithm for minimization (new test version)
-sdonly       do delta method for std dev estimates without redoing hessian
-? or -help   this message
```

The version of AD Model Builder is printed. this can be useful to determine the version which the application was compiled with.

```
-aind NAME
```

By default the program named `xxxx(.exe)` tries to read in its data from the file `xxxx.dat`. This option changes the data file to `NAME`.

`-ainp NAME`

This option changes the file from which the initial parameter estimates are read in when to `NAME`. The program expects the parameters to be in ASCII format with comment lines beginning with `#`.

When a program is running it produces parameter estimates in ASCII format in files named `xxxx.p01`, ..., `xxxx.par`. These files are in the proper format to be input back into the model and permit restarts at any phase of the minimization.

`-binp NAME`

This option changes the file from which the initial parameter estimates are read in when to `NAME`. The program expects the parameters to be in binary format.

When a program is running it produces parameter estimates in binary format in files named `xxxx.b01`, ..., `xxxx.bar`. These files are in the proper format to be input back into the model and permit restarts at any phase of the minimization.

Both ASCII and binary forms of the parameter files are supplied because they have different advantages and disadvantages. ASCII files can be easily examined and edited. Binary files supply parameter values to the limit of machine precision in a compact format.

`-lmn N`

The limited memory Newton minimization option reduces the amount of memory necessary for holding the approximate Hessian inverse. It is of use particularly in problems with a large number of parameters (typically  $> 1000$ ). For many problems it is not as efficient per function evaluation as the default quasi-Newton method although this is not always the case. `N` is the number of past steps of information kept for the quasi-Newton update. Typically a value of about 5-20 is good.

`-lprof`

This option turns on the profile likelihood calculations. A variable for which profile likelihood calculations are performed must have been declared with the `likeprof_number` in the TPL file.

`-prsave`

This option causes the values of the independent variables for the profile likelihood points to be saved in a file named `xxx.pvl` where `xxx` is the name of the variable being profiled. These values can be used later for starting the MCMC analysis at different values which is useful for testing the mixing of the chain with respect to that parameter.

`-maxph N`

You may want to add extra phases to the minimization – usually because the standard set of phases has not converged. This will set the number of phases to N.

`-mcmc [N]`

This option turns on the the calculation of the Markov chain Monte Carlo routine. By default the model will recalculate the approximate Hessian so you may want to use the `-nohess` option if you don't wish to recalculate the Hessian. It is your responsibility to ensure that the Hessian data in the current directory are current. The `mcmc` routine will perform N simulations.

`-mcr`

Restart (and continue) a previous Markov chain Monte Carlo routine. This will continue from where the previous routine left off.

`-mcsave N`

For the usual MCMC routine the results from consecutive steps of the simulation are highly correlated. If the parameters of interest are expensive to compute it may be advantages to only compute every N'th one. This option saves the results so that they can be used in subsequent calculations.

`-mcsave N`

This option will use the previously save results from MCMC to evaluate parameters of interest. The function `mceval_phase()` can be useful here to only calculate the parameters during this phase.

`-nox`

This option suppresses the printing of the current x vector being sampled by the function minimizer. Printing this out can be a significant overhead for models with a large number of parameters – also it simply irritates some users.



## Chapter 12

# All the functions in AD Model Builder

This chapter attempts to list and document all the functions available in AD Model Builder. It will always be incomplete since functions are continually being added. If you are aware of a function which is not documented please contact me at [otter@otter-rsch.com](mailto:otter@otter-rsch.com) and let me know.

### Naming conventions for documenting functions

Wherever applicable the name function has been supplied for constant and variable objects (such as `double` and `dvariable`). Instead of repeating the description for both kinds of objects the convention of referring to both types as “number”, “vector”, “matrix”, etc. will be observed.

### Mathematical Functions

The following functions have been included in AUTODIF by overloading the C++ library functions

```
sin cos tan asin atan acos sinh cosh tanh fabs (sfabs) exp log log10 sqrt pow  
gammln log_comb
```

These functions can be used on numbers or `vector_objects` in the form

```
number = function(number);  
vector_object = function(vector_object);
```

When operating on `vector_objects` the functions operate element by element, so that if `y` is a `dvector` whose elements are  $(y_1, \dots, y_n)$  then `exp(y)` is a `dvector` whose elements are  $(\exp(y_1), \dots, \exp(y_n))$ .

The functions `min` and `max` when applied to a `vector_object` return a `number` which is equal to the minimum or maximum element of the `vector_object`

The function `gammln` is the logarithm, of the gamma function.

The function `log_comb(n,k)` is the logarithm, of the function the combination of `n` things taken `k` at a time. It is defined via the logarithm of the gamma function for non-integer values and is differentiable.

## operations on arrays

There are several operations familiar to users of spreadsheets which do not appear as often in classical mathematical calculations. For example spreadsheet users often wish to multiply one column in a spreadsheet by the corresponding elements of another column. Spread sheet users might find it much more natural to define the product of matrices as an element-wise operation such as

$$z_{ij} = x_{ij} * y_{ij}$$

The “classical” mathematical definition for the matrix product has been assigned to the overloaded operator “\*” so that large mathematical formulas involving vector and matrix operations can be written in a concise notation. Typically, spreadsheet-type calculations are not so complicated and do not suffer so much from being forced to adopt a “function-style” of notation.

Since addition and subtraction are already defined in an element-wise manner, it is only necessary to define element-wise operations for multiplication and division. We have name these functions `elem_prod` and `elem_div`.

```
vector_object = elem_prod(vector_object,vector_object) // element-wise multiply
```

$$z_i = x_i * y_i$$

```
vector_object = elem_div(vector_object,vector_object) // element-wise divide
```

$$z_i = x_i / y_i$$

```
matrix_object = elem_prod(matrix_object,matrix_object) // element-wise multiply
```

$$z_{ij} = x_{ij} * y_{ij}$$

```
matrix_object = elem_div(matrix_object,matrix_object) // element-wise divide
```

$$z_{ij} = x_{ij} / y_{ij}$$

## The identity matrix function `identity_matrix`

```
matrix_object = identity_matrix(int min,int max)
```

Creates a square identity matrix with minimum valid indices `min` and maximum valid index `max`.

## The operations `det inv norm norm2 min max sum`

The determinant of a matrix object (The matrix must be square, that is the number of row must equal the number of columns)

```
matrix_object = det(matrix_object)
```

The inverse of a matrix object (The matrix must be square, that is the number of row must equal the number of columns)

```
matrix_object = inv(matrix_object)
```

The norm of a vector\_object

```
number = norm(vector_object)
```

$$z = \sqrt{\sum_i x_i^2}$$

The norm squared of a vector\_object

```
number = norm2(vector_object)
```

$$z = \sum_i x_i^2$$

The norm of a matrix\_object

```
number = norm(matrix_object)
```

$$z = \sqrt{\sum_{ij} x_{ij}^2}$$

The norm squared of a matrix\_object

```
number = norm2(matrix_object)
```

$$z_{ij} = x_{ji}$$

The transpose of a matrix\_object

```
matrix_object = trans(matrix_object)
```

$$z = \sum_{ij} x_{ij}^2$$

The sum over the elements of a vector object

```
number = sum(vector_object)
```

$$z = \sum_i x_i$$

The row sums of a matrix object

```
vector = rowsum(matrix_object)
```

$$z_i = \sum_j x_{ij}$$

The column sums of a matrix object

```
vector = colsum(matrix_object)
```

$$z_j = \sum_i x_{ij}$$

The minimum element of a vector object

```
number = min(vector_object)
```

The maximum element of a vector object

```
number = max(vector_object)
```

## Eigenvalues and eigenvectors of a symmetric matrix

While we have included eigenvalue and eigenvector routines for both constant and variable matrix objects you should be aware that in general the eigenvectors and eigenvalues are not differentiable functions of the variables determining the matrix.

The eigenvalues of a symmetric matrix

```
vector_object = eigenvalues(matrix_object)
```

are returned in a vector. It is the users responsibility to ensure that the matrix is actually symmetric. The routine symmetrizes the matrix so that the eigenvalues returned are actually those for the symmetrized matrix.

The eigenvectors of a symmetric matrix

```
matrix_object = eigenvectors(matrix_object)
```

are returned in a matrix. It is the users responsibility to ensure that the matrix is actually symmetric. The routine symmetrizes the matrix so that the eigenvectors returned are actually those for the symmetrized matrix. The eigenvectors are located in the columns of the matrix. The  $i$ 'th eigenvalue returned by the function `eigenvalues` corresponds to the  $i$ 'th eigenvector returned by the function `eigenvector`.



## The choleski decomposition of a positive definite symmetric matrix

For a positive definite symmetric matrix **S**, the choleski decomposition of **S** is a lower triangular matrix **T** satisfying the relationship  $S=T*\text{trans}(T)$ . If **S** is a (positive definite symmetric) matrix object and **T** is a matrix object, the line of code

```
T=choleski_decomp(S);
```

will calculate the choleski decomposition of **S** and put it into **T**.

## Solving a system of linear equations

If **y** is a vector and **M** is an invertible matrix then finding a vector **x** such that

```
x=inv(M)*y
```

will be referred to as solving the system of linear equations determined by **y** and **M**. Of course it is possible to use the `inv` function to accomplish this task but it is much more efficient to use the `solve` function.

```
vector x=solve(M,y); // x will satisfy x=inv(M)*y;
```

It turns out that it is a simple matter to calculate the determinant of the matrix **M** at the same time as the system of linear equations is solved, and since this is useful in multivariate analysis we have also included a function which returns the determinant at the same time as the system of equations is solved. To avoid floating point overflow or underflow when working with large matrices the logarithm of the absolute value of the determinant together with the sign of the determinant are returned. The constant form of the solve function is

```
double ln_det;  
double sign;  
dvector x=solve(M,y,ln_det,sign);
```

while the variable form is

```
dvariable ln_det;  
dvariable sign;  
dvar_vector x=solve(M,y,ln_det,sign);
```

The solve function is useful for calculating the log-likelihood function for a multivariate normal distribution. Such a log-likelihood function involves a calculation similar to

```
l = -.5*log(det(S)) -.5*y*inv(S)*y
```

where **S** is a matrix object and **y** is a vector object. It is much more efficient to carry out this calculation using the solve function. The following code illustrates the calculations for variable objects.

```
dvariable ln_det;
```

```

dvariable sign;
dvariable l;
dvar_vector tmp=solve(M,y,ln_det,sign);
l=-.5*ln_det-y*tmp;

```

## Methods for filling arrays and matrices

While it is always possible to fill vectors and matrices by using loops and filling them element by element, this is tedious and prone to error. To simplify this task a selection of methods for filling vectors and matrices with random numbers or a specified sequence of numbers is available. There are also methods for filling row and columns of matrices with vectors. In this section the symbol `vector` can refer to either a `dvector` or a `dvar_vector`, while the symbol `matrix` can refer to either a `dmatrix` or a `dvar_matrix`.

```
void vector::fill("{m,n,...}")
```

fills a vector with a sequence of the form `n, m, ...`. The number of elements in the string must match the size of the vector.

```
void vector::fill_seqadd(double& base, double& offset)
```

fills a vector with a sequence of the form `base, base+offset, base+2*offset, ...`

For example if `v` is a `dvector` created by the statement

```
dvector v(0,4);
```

then the statement

```
v.fill_seqadd(-1,.5);
```

will fill `v` with the numbers  $(-1.0, -0.5, 0.0, 0.5, 1.0)$ .

```
void matrix::rowfill_seqadd(int& i,double& base, double& offset)
```

fills row `i` of a matrix with a sequence of the form `base, base+offset, base+2*offset, ...`

```
void matrix::colfill_seqadd(int& j,double& base, double& offset)
```

fills column `j` of a matrix with a sequence of the form `base, base+offset, base+2*offset, ...`

```
void matrix::colfill(int& j,vector&)
```

fills the `j`'th column of a matrix with a vector

```
void matrix::rowfill(int& i,vector&)
```

fills the `i`'th row of a matrix with a vector

## Methods for filling arrays and matrices with random numbers

This method of filling containers with random numbers is becoming obsolete. The preferred method is to use the `random_number_generator` class. See section 12.15 for instructions on using this class. In this section a uniformly distributed random number is assumed to have a uniform distribution on  $[0, 1]$ . A normally distributed random number is assumed to have mean 0 and variance 1. A binomially distributed random number is assumed to have a parameter  $p$  where 1 is returned with probability  $p$  and 0 is returned with probability  $1 - p$ . A multinomially distributed random variable is assumed to have a vector of parameters  $P$  where  $i$  is returned with probability  $p_i$ . If the components of  $P$  do not sum to 1 the vector will be normalized so that the components do sum to 1.

```
void vector::fill_randu(long int& n)
```

fills a vector with a sequence of uniformly distributed random numbers. The `long int n` is a seed for the random number generator. Changing `n` will produce a different sequence of random numbers. This function is now obsolete. You should use the `random_number_generator` class to generate random numbers.

```
void matrix::colfill_randu(int& j, long int& n)
```

fills column `j` of a matrix with a sequence of uniformly distributed random numbers. The `long int n` is a seed for the random number generator. Changing `n` will produce a different sequence of random numbers.

```
void matrix::rowfill_randu(int& i, long int& n)
```

fills row `i` of a matrix with a sequence of uniformly distributed random numbers

```
void vector::fill_randbi(long int& n, double& p)
```

fills a vector with a sequence random numbers from a binomial distribution.

```
void vector::fill_randn(long int& n)
```

fills a vector with a sequence of normally distributed random numbers. This function is now obsolete. You should use the `random_number_generator` class to generate random numbers.

```
void matrix::colfill_randn(int& j, long int& n)
```

fills column `j` of a matrix with a sequence of normally distributed random numbers

```
void matrix::rowfill_randn(int& i, long int& n)
```

fills row `i` of a matrix with a sequence of normally distributed random numbers

```
void vector::fill_multinomial(long int& n, dvector& p)
```

fills a vector with a sequence random numbers from a multinomial distribution. The parameter  $p$  is a `dvector` such that  $p[i]$  is the probability of returning  $i$ . The elements of  $p$  must sum to 1.

## Methods for obtaining shape information from containers

When this code was first written the maximum dimension of arrays was about 4. At this level it perhaps make sense to think of a one dimensional array as a vector, a two dimensional array as a matrix etc. For a matrix one thinks in terms of rows and columns. However with the adoption of ragged container objects up to eight dimensions (at present) a more generic method of obtaining shape information of these objects was called for.

If `v` is a vector object then

```
int v.indexmin()
int v.indexmax()
```

return the minimum and maximum valid indices for `v`. If `m` is a matrix object then

```
int v.rowmin()
int v.rowmax()
int v.colmin()
int v.colmax()
```

return the minimum and maximum valid row and column indices for `m`. These functions make sense for a matrix where every row is a vector with the same minimum and maximum valid indices. For a ragged matrix this is no longer the case so that the `rowmin` and `rowmax()` functions don't make sense in this case. To deal with a ragged matrix one may need to calculate the minimum and maximum valid indices for each row of the ragged matrix. To facilitate this approach the functions `indexmin` and `indexmax` have been defined for all container classes so that for example if `w` is a six dimensional array then

```
int w.indexmin()
int w.indexmax()
```

return the minimum and maximum valid indices for the first index of `w`. For a matrix object `m` `m.indexmin()` and `m.colmin()` are the same and as long as `m` is not ragged then `m(m.indexmin()).indexmin()` is the same as `m.colmin()` and `m(m.indexmin()).indexmax()` is the same as `m.colmax()`.

## Methods for extracting from arrays and matrices

```
vector column(matrix& M,int& j)
```

extracts the `j`'th column from a matrix and puts it into a vector

```
vector extract_row(matrix& M,int& i)
```

extracts a row from a matrix and puts it into a vector. Note that the operation `M(i)` has the same effect.

```
vector extract_diagonal(matrix& M)
```

extracts the diagonal elements from a matrix and puts them into a vector.

The function call operator ( ) has been overloaded in two ways to provide for the extraction of a subvector.

```
vector(ivector&)
```

An `ivector` object is used to specify the elements of the vector to be chosen. If `u` and `v` are `dvector`s and `i` is an `ivector` the construction

```
dvector u = v(i);
```

will extract the members of `v` indexed by `i` and put them in the `dvector u`. The size of `u` is equal to the size of `i`. The `dvector u` will have minimum valid index and maximum valid index equal to the minimum valid index and maximum valid index of `i`. The size of `i` can be larger than the size of `v` in which case some elements of `v` must be repeated. The elements of the `ivector i` must lie in the valid index range for `v`.

If `v` is a `dvector` and `i1` and `i2` are two integers

```
u(i1,i2)
```

is a `dvector` which is a subvector of `v` (provided of course that `i1` and `i2` are valid indices for `v`). Subvectors can appear on both the left and right hand side of an assignment.

```
dvector u(1,20);
dvector v(1,19);
v = 2.0; // assigns the value 2 to all elements of v
u(1,19) = v; // assigns the value 2 to elements 1 through 19 of u
```

In the above example suppose that we wanted to assign the vector `v` to elements 2 through 20 of the vector `u`. To do this we must first ensure that they have the same valid index ranges. The operators `++` and `--` increment and decrement the index ranges by 1. The code fragment

```
dvector u(1,20);
dvector w(1,19);
dvector v(1,19);

v = 2.0; // assigns the value 2 to all elements of v

--u(2,20) = v; // assigns the value 2 to elements 2 through 20 of u

u(2,20) = ++v; // assigns the value 2 to elements 2 through 20 of u
// probably not what you want
w=v; // error different index ranges
```

It is important to realize that from the point of view of the vector `u` both of the above assignments have the same effect. It will have elements 2 through 20 set equal to 2. The difference is in the side effects on the vector `v`. The operation `++v` will increase the minimum and maximum valid index range of the vector `v` by one. This increase is permanent. On the other hand the operation `--u(2,20)` decrements the valid index bounds of the *subvector*

`u(2,20)`. This is a distinct object from the vector `u` although both objects share a common area for their components. Thus the valid index bounds of `u` are not effected by this process. The use of subvectors and increment and decrement operations can be used to remove loops from the code. Note that

```
dvector x(1,n)
dvector y(1,n)
dvector z(1,n)
for (int i=2;i<=n;i++)
{
    x(i)=y(i-1)*z(i-1);
}
```

can be written as

```
dvector x(1,n)
dvector y(1,n)
dvector z(1,n)
x(2,n)=++elem_prod(y(1,n-1),z(1,n-1)); // elem_prod is element-wise
// multiplication of vectors
```

This `shift` function can be used to set the minimum (and maximum) valid index for a vector.

```
dvector u(10,100); // minimum valid index is 10
// maximum valid index is 100
u.shift(25); // minimum valid index is 25
// maximum valid index is 115
```

In particular the operators `--` and `++` are just convenient shorthand for using the `shift` function to change the minimum valid index by 1.

```
dvector u(10,100); // minimum valid index is 10
// maximum valid index is 100
u.shift(u.indexmin()-1); // minimum valid index is 9
--u; // same result as u.shift(u.indexmin()-1)
u.shift(u.indexmin()+1); // minimum valid index is 11
++u; // same result as u.shift(u.indexmin()+1)
```

## Sorting vectors and matrices

While sorting is not strictly a part of methods for calculating the derivatives of differentiable functions (it is a highly non-differentiable operation) it is so useful for pre- and post-processing data that we have included some functions for sorting `dvector` and `dmatrix` objects. If `v` is a `dvector` the statement

```
dvector w=sort(v);
```

will sort the elements of `v` in ascending order and put them in the `dvector` object `w`. The minimum and maximum valid indices of `w` will be the same as those of `v`. If desired an index table for the sort can be constructed by passing an `ivector` along with the `dvector`. This

index tables can be used to sort other vectors in the same order as the original vector by using the ( ) operator.

```
dvector u={4,2,1};
dvector v={1,6,5}
ivector ind(1,3);
dvector w=sort(u,ind); // ind will contain an index table for the sort
// Now w=(1,2,4) and ind=(3,2,1)
dvector ww=v(ind);    // This is the use of the ( ) operator for subset
                        // selection.
// Now ww=(5,6,1)
```

The sort function for a `dmatrix` object sort the columns of the `dmatrix` into ascending order, using the column specified to do the sorting. For example

```
dmatrix MM = sort(M,3);
```

will put the sorted matrix into `MM` and the third column of `MM` will be sorted in ascending order.

## Statistical Functions

```
cumd_norm
inv_cumd_norm
cumd_cauchy
inv_cumd_cauchy
```

The cumulative distribution function and the inverse cumulative distribution function for the normal and cauchy distributions.

## The random number generator class

The random number generator class is used to manage the generation of random numbers. A random number generator object is created with the declaration

```
random_number_generator r(n);
```

where `n` is the seed which initializes the random number generator. Any number of random number generators may be declared. This class can be used to manage random number generation with the following functions.

```
randpoisson(lambda,r); // generate a poisson with parameter lambda
randn(r);              // generate a normally distributed random number
randu(r);              // generate a uniformly distributed random number
v.fill_randu(r)        // fill a vector v
v.fill_randn(r)        // fill a vector v
v.fill_randpoisson(lambda,r) // fill a vector v
v.fill_multinomial(r,p) // fill a vector v
                        // p is a vector of probabilities
m.fill_randu(r)        // fill a matrix m
m.fill_randn(r)        // fill matrix m
m.fill_randpoisson(lambda,r) // fill a matrix m
```

The incomplete beta function  $I_x(a, b)$  is defined by

$$I_x(a, b) = \frac{1}{B(a, b)} \int_0^x t^{a-1} (1-t)^{b-1} dt \quad (a, b, > 0) \quad (12.1)$$

This is also the cumulative distribution function for the beta family of probability distributions. The function is named `betai` and is invoked by

```
.....  
dvariable p=betai(a,b,x);
```



## Chapter 13

# Advanced Features of AD Model Builder

### Using other class libraries in AD Model Builder programs

A useful feature of C++ is its open nature. This means that the user can combine several class libraries into one program. In general this simply involves including the necessary header files in the program and then declaring the appropriate class instances in the program. Instances of external classes can be declared in AD Model Builder program in several ways. They can always be declared in the procedure or report section of the program as local objects. It is sometimes desired to include instances of external classes in a more formal way into an AD Model Builder program. This section describes how to include them into the `DATA_SECTION` or `PARAMETER_SECTION`. After that they can be referred to as though they were part of the AD Model Builder code (except for the technicalities to be discussed below).

AD Model Builder employs a strategy of late initialization of class members. The reason for this is to allow time for the user too carry out any calculations which may be necessary for determining parameter values etc. which are used in the initializatin of the object. Because of the nature of constructors in C++ this means that every object declared in the `DATA_SECTION` or the `PARAMETER_SECTION` must have a default constructor which takes no arguments. The actual allocation of the object is carried out by a class member function named `allocate` which takes any desired arguments. Since external classes will not generally satisfy these requirments a different strategy is employed for these classes. A pointer to the object is included in the appropriate AD Model Builder class. This pointer has the prefix `pad_` inserted before the name of the object. The pointer to `myobj` would have the form `pad_myobj`.

```
!!CLASSfooclass myobj( .... )
```

The user can refer to the object in the code simply by using its name.

## Appendix 1 – The regression function

The `robust_regression` function calculates the log-likelihood function for the standard statistical model of independent normally distributed errors with mean 0 and equal variance. The code is written in terms of AUTODIF objects such as `dvariable` and `dvar_vector`. They are described in the AUTODIF User's Manual.

```
dvariable regression(const dvector& obs,const dvar_vector& pred)
{
  double nobs=double(size_count(obs)); // get the number of
                                        // observations
  dvariable vhat=norm2(obs-pred); // sum of squared deviations
  vhat/=nobs; //mean of squared deviations
  return (.5*nobs*log(vhat)); //return log-likelihood value
}
```

## Appendix 2 – AD Model Builder types

The effect of a declaration depends on whether it occurs in the `DATA_SECTION` or in the `PARAMETER_SECTION`. Objects declared in the `DATA_SECTION` are constant, that is like data. Objects declared in the `PARAMETER_SECTION` are variable, that is like the parameters of the model which are to be estimated. Any objects which depend on variable objects must themselves be variables objects, that is they are declared in the `PARAMETER_SECTION` and not in the `DATA_SECTION`.

In the `DATA_SECTION` the prefix `init_` indicates that the object is to be read in from the data file. In the `PARAMETER_SECTION` the prefix indicates that the object is an initial parameter whose value will be used to calculate the value of other (non initial) parameters. In the `PARAMETER_SECTION` initial parameters will either have their values read in from a parameter file or will be initialized with their default initial values. The actual default values used can be modified in the `INITIALIZATION_SECTION`. From a mathematical point of view objects declared with the `init_` prefix are independent variables which are used to calculate the objective function being minimized.

The prefixes `bounded_` and `dev_` can only be used in the `PARAMETER_SECTION`. The prefix `bounded_` restricts the numerical values which an object can take on to lie in a specified bounded interval. The prefix `dev_` can only be applied to the declaration of vector objects. It has the effect of restricting the sum of the individual components of the vector object to sum to 0.

The prefix `sdreport_` can only be used in the `PARAMETER_SECTION`. An object declared with this prefix will appear in the covariance matrix report. This provides a convenient method for obtaining estimates for the variance of any parameter which may be of interest. Note that the prefixes `sdreport_` and `init_` can not both be applied to the same object. There is no need to do so since initial parameters are automatically included in the standard

deviations report. AD Model Builder also has three and four dimensional arrays. They are declared like

```
3darray dthree(1,10,2,20,3,10)
4darray df(1,10,2,20,3,10)
init_3darray dd(1,10,2,20,3,10) // data section only
init_4darray dxx(1,10,2,20,3,10) // data section only
```

The following table contains a summary of declarations and the types of objects associated with them in AD Model Builder. The types `dvariable`, `dvector`, `dmatrix`, `d3_array`, `dvar_vector`, `dvar_matrix`, and `dvar3_array` are described in the AUTODIF Users's manual.

declaration	type of object in DATA_SECTION	type of object in PARAMETER_SECTION
[init_]int	int	int
[init_][bounded_]number	double	dvariable
[init_][bounded_][dev_]vector	vector of doubles(dvector)	vector of dvariables(dvar_vector)
[init_][bounded_]matrix	matrix of doubles(dmatrix)	matrix of dvariables(dvar_matrix)
[init_]3darray	3 dimensional array of doubles	3 dimensional array of dvariables
4darray	4 dimensional array of doubles	4 dimensional array of dvariables
5darray	5 dimensional array of doubles	5 dimensional array of dvariables
6darray	6 dimensional array of doubles	6 dimensional array of dvariables
7darray	7 dimensional array of doubles	7 dimensional array of dvariables
sdreport_number	na	dvariable
likeprof_number	na	dvariable
sdreport_vector	na	vector of dvariables(dvar_vector)
sdreport_matrix	na	matrix of dvariables(dvar_matrix)

## Appendix 3 – The profile likelihood

We have been told that the profile likelihood as calculated in AD Model Builder for dependent variables may differ from that calculated by other authors. This section will clarify what we mean by the term and motivate our calculation.

Let  $(x_1, \dots, x_n)$  be  $n$  independent variables,  $f(x_1, \dots, x_n)$  be a probability distribution and  $g$  denote a dependent variable that is a real valued function of  $(x_1, \dots, x_n)$ . Fix a value  $g_0$  for  $g$  and consider the integral

$$\int_{\{x: g_0 - \epsilon/2 \leq g(x) \leq g_0 + \epsilon/2\}} f(x_1, \dots, x_n)$$

which is the probability that  $g(x)$  has a value between  $g_0 - \epsilon/2$  and  $g_0 + \epsilon/2$ . This probability depends on two quantities, the value of  $f(x)$  and the thickness of the region being integrated over. We approximate  $f(x)$  by its maximum value  $\hat{x}(g) = \max_{x: g(x)=g_0} \{f(x)\}$ . For the

thickness we have  $g(\hat{x} + h) \approx g(\hat{x}) + \langle \nabla g(\hat{x}), h \rangle = \epsilon/2$  where  $h$  is a vector perpendicular to the level set of  $g$  at  $\hat{x}$ . However  $\nabla g$  is also perpendicular to the level set so  $\langle \nabla g(\hat{x}), h \rangle = \|\nabla g(\hat{x})\| \|h\|$  so that  $\|h\| = \epsilon / (2\|\nabla g(\hat{x})\|)$ . Thus the integral is approximated by  $\epsilon f(\hat{x}) / \|\nabla g(\hat{x})\|$  and taking the derivative with respect to  $\epsilon$  yields  $f(\hat{x}) / \|\nabla g(\hat{x})\|$  which is the profile likelihood expression for a dependent variable.

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Gelman, Andrew., John B. Carlin, Hal S. Stern, and Donald B. Rubin. Bayesian Data Analysis. Chapman and Hall.

Hilborn, Ray and Carl Walters. Quantitative Fisheries Stock Assessment and Management: Choice, Dynamics, and Uncertainty. 1992.

## How to order AD Model Builder

AD Model Builder bundled with AUTODIF is available for a wide variety of compilers on 80386 computers including Borland C++, Visual C++(32 bit) and the "GNU" C++ compiler DJGPP Other compilers are supported at present on Linux, SUN, HP, and SGI UNIX workstations. It is important that you tell us the exact form of your hardware and version of your compiler for UNIX. Multi-user and site licenses are available. Contact

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# Chapter 14

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