Brief User's Guide:
Dynamic Systems Estimation Library

Paul Gilbert, December 2001.

The software documented in this guide is available by following the links to DSE at <*http://www.bank-banque-canada.ca/pgilbert*>. Please check there for new versions.

This draft reflects many changes which were incorporated in October 1999. Due to these changes, the 1996 version of the guide gives a better description of any version of the code prior to October 1999. I have tested the version of the code described here (December 2001) with Splus 3.3 on Solaris and with R 1.4.0 (pre-release) on Solaris and Linux. I believe everything should work with Splus 3.4 but I have not tested it. There are known problems with Splus 5. Please report errors you find.

Caveat: This software is the by-product of ongoing research. It is not a commercial product. Limited effort is put into maintaining the documentation. There may be references to functions which do not yet work and/or have not been distributed, and the documentation may not correspond to the current capabilities of the functions. While the software does many standard time-series things, it is really intended for doing some non-standard things. The main difference between this library and many widely available packages is that the library is designed for studying estimation techniques and modeling techniques. If your interest is simply in simulation of time-series models or in estimation with well established techniques, you may find many commercial products which are better. If your interest is in new techniques and time-series research then you will find that this software is very good, both because of the design and because you have direct access to the code, so you can add your own functions and make changes. In addition, the S and R languages are very powerful for doing statistical calculations. Direct access to the code and function results may also make the software useful for teaching purposes.

In an effort to foster communications among users, I have set up an e-mail list for questions and discussion of problems. To subscribe to the list send a message to <*boc_list@bank-banque-canada.ca*> with a line in the body:

subscribe boc_dse Your Name

Subsequent message to the list should be sent to <*boc_dse@bank-banque-canada.ca*>. Constructive suggestions and comments are welcomed. I can be reached at <*pgilbert@bank-banque-canada.ca*> or at <*PaulGilbert@Ottawa.com*> or by phone at (613) 782-7346.

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1. Introduction

The functions in this library are designed for studying multi-variate time-series models and estimation techniques. The library was originally designed with linear, time-invariant auto-regressive moving-average (ARMA) models and state-space (SS) models in mind. These remain the most well developed models in the library and provide the basis for most of the examples in this guide. However, the library implements object oriented methods for studying new estimation techniques and other kinds of time series models. Methods are implemented for studying Troll (Intex Solutions, Inc.) models (currently broken) and some neural net architectures are being explored. These provide examples for implementing new model objects and estimation methods. Users are encouraged to consider specific representations used in this guide as examples in the context of the library's broader objectives.

In order to provide examples the library also implements some estimation techniques and methods for converting among various representations of time series models. Many functions for the usual diagnostics which are preformed with time series data and models are included as well. Additional information on specific functions is available through the help facility. For details of some of the underlying theory of ARMA and SS model equivalence and examples of some of the capabilities of the library see Gilbert (1993). For examples of using the library to evaluate estimation methods see Gilbert (1995). Examples of the use of several functions are illustrated in the files in the demo subdirectories. (In R see *demo()*)

2. Getting Started with S/R

This library works with the Splus (MathSoft <*http:www.insightful.com*>) version of the S language and the similar R language (Ihaka and Gentleman, 1996) <*http://cran.r-project.org*>. The notation S/R will be used to indicate both languages and S or R will be used when a remark is specific to one or the other. Splus will be indicated when a remark may be specific to Splus but not to S in general. Italics will be used to indicate examples as well as functions and objects, and *()* will frequently be added to function names to help distinguish them as such. Anything entered after a # is a comment in S/R.

This guide tries to explain certain aspects of S/R in order to make the library accessible to users unfamiliar with S/R. However, knowledge of the S/R language is extremely useful. Users are referred to Becker, Chambers and Wilks (1988, commonly known as *The Blue Book*), Venables and Ripley (various editions), Ripley (1994), Burns(...), Krause and Olson(...), or to the user manuals for their implementation. Users already familiar with S/R please ignore the simplified explanations given here.

An important point is that S/R functions take arguments in brackets *(...)*, even when there are no argument. So, for example, the function to get out of S/R and back to the operating system is *q()*. Values are assigned to S/R variables with the two character symbol "*<-*" or the one character underscore symbol "_". Also, it is important to be aware that upper and lower case letters are different. Most examples in this guide show only the user input, not the computer output.

If DSE is not installed on your system, please see the appendix on installation. Once S/R is started the DSE library must be made available. In S this is done with:

library("DSE", first=T)
load.DSE.fortran()

or in R by:

library("dse1") #for the base functionality. (This also attaches syskern and tframe.)
library("dse2") #for functions described later in the guide.
library("padi") #for database interface.
library("dsepadi") #for the dse layer on top of database interface.
library("monitor") #for monitoring model functions described later in the guide.
library("juice") #for functions (not yet described in the guide)
library("curve") #for functions (not yet described in the guide)

You should consider putting these lines in your *.Firs*t function, which is automatically executed each time you start. (This is especially advisable in Splus as some of the more computationaly intensive functions in this library spawn separate Splus sessions to speed calculations.)

Descriptions of functions and objects are available in the help system. This is integrated with the R help system which is started by

help.start()

HTML help is available in S and can be viewed with a web browser. From an S session the help facility can be started with the function

help.start.DSE() # tries to start Netscape by default
help.start.DSE(browser= "my.browser")

The string passed as *browser* should be a system command for starting a web (HTML) browser.

3. General Outline of DSE Objects and Methods

The library implements three main classes of objects: *TSdata*, *TSmodel*, and *TSestModel*. These are respectively, representations of data, models, and models with data and estimation information.

TSdata is an object which contains a (multivariate) time series object called *output* and optionally another called *input*. Methods for defining the general version of this class of object are described in the next section and more details are provided in the help for *TSdata*. Input and output correspond to what are often labelled *x* and *y* in econometrics and time series discussions of ARMA models. These are sometimes called exogenous and endogenous variables, though those terms are often not correct for these models. Statistically, output is the variable which is modelled and input is the conditioning data. From a practical and computational point of view, the model forecasts output data and input data must always be supplied. In particular, to forecasts multiple periods into the future requires that input data for the future must be supplied so that the model can calculate outputs. The terms input and output are commonly used in the engineering literature, and often correspond to a control variable and the output from a physical system. However, the causal interpretation in this context is not always appropriate for other uses of time series models. In addition, even when a causal direction is known or assumed, it is not always desirable to define the exogenous variable as an input. If the model is to give forecasts into the future then it may be better to define exogenous variables as outputs and let the model forecast them, unless better forecasts of the exogenous variables are available from other sources. One context in which an input variable is important is to examine policy scenarios. In this context the policy variable is defined as the input and forecasts are produced conditioned on different assumptions about the policy.

TSmodel objects are models which are arranged to use *TSdata*. These objects always have another specific class indicating the type of model. The *ARMA* and *SS* constructor methods for ARMA *TSmodel*s and state-space *TSmodel*s are described in a section below. Other specific classes of *TSmodel*s can be defined and many of the methods in this library will work with these new models, as long as they use *TSdata* and have a few important methods implemented. More details on defining other classes of models are given in a later section of this guide. Details on the representation of models are provided in the help for *TSmodel* and the help for specific model constructors.

TSestModel objects are objects which contain *TSdata*, a *TSmodel*, and some statistical information generated by *l(model, data)*. The *l()* method originally meant likelihood, but the method returns the one-step-ahead predictions and other information based on those predictions. Methods for studying one-step-ahead model forecasts extract the predictions from these objects. Other methods treat *TSestModel* objects as a simple way to group together a model and data. For example, methods for studying multi-step forecasts need to generate the forecasts, so they do not use the predictions in the *TSestModel* object. More detail about *TSestModel* objects is available in the help system.

The default method for *TSdata()* constructs a *TSdata* object, as will be described in the next section. The generic methods *TSmodel()* and *TSdata()* can also be used to extract the *TSmodel* or *TSdata* object from another object (such as a *TSestModel*).

The functions in this library can be used by starting with data and estimating a model, or by starting with a model and producing simulated data. The next section describes *TSdata* objects, but it would be equally possible to start with models as described in the sections following.

4. Defining a TSdata Structure

Several data sets are included with this library and will be used in examples in this guide. In S these are available when the library is attached. In R they are made available by

data(package="dse1") # to see the names of the data sets
data(xxx, package="dse1") # replace xxx by the name of the data set to be made available

This section describes how to construct a *TSdata* structure if you have other data you would like to use. Section 10 discusses adding new kinds of TSdata classes. Some installations may have an online database and it may be possible to connect directly to this data. An appendix on TSPADI data retrieval gives more detail on one possibility for doing this.

For many people the situation will be that the data is in some ASCII file. This can be loaded into session variables with a number of standard S/R functions, the most useful of which are probably *scan()* and *read.table()*. Following is an example which reads data from an ASCII file called *eg1.dat* and puts it in the variable called *eg1.DSE.data* (which is also one of the available data sets). The ASCII file is distributed with this library and can be found in the data directory below where the library is installed. The value of the variable *DSE.HOME* should indicate where the library is installed, so *paste(DSE.HOME, "/data/eg1.dat", sep="")* will give the location of the file. The file has five columns of numbers and 364 rows. The first column just enumerates the rows and is discarded.

*eg1.DSE.data <- t(matrix(scan(paste(DSE.HOME, "/data/eg1.dat", sep="")),
5, 364))[, 2:5]*

This matrix can be used to form a *TSdata* object by

*eg1.DSE.data <- TSdata(input= eg1.DSE.data[,1,drop = F],
output=eg1.DSE.data[, 2:4, drop = F])*

The matrix and the resulting *TSdata* object do not have a good time scale associated with points. A better time scale can be added by

eg1.DSE.data <-tframed(eg1.DSE.data, list(start=c(1961,3), frequency=12))

There are several different possibilities for representing time in S/R objects. The most common is the *ts* matrix object, which is used in the above default *tframed* method. (*ts* is not truly a class of object in S, since it is the default representation of time series which existed before classes were introduced.) The above *tframed* method and *ts* can also be used directly on the matrix before the *TSdata* object is formed. However, [,] in Splus results in the time scale being lost, so it would need to be reassigned to the *input* and *output* matrices of the *TSdata* object. The methods from the tframe library are used extensively in the DSE library because they provide a common way to proceed in Splus and R, extend to other time representations in addition to *ts*, and provide a mechanism for extending methods to other objects like *TSdata* and *TSmodels*.

Names can be given to the series with

seriesNamesInput(eg1.DSE.data) <- "R90"
seriesNamesOutput(eg1.DSE.data) <- c("M1","GDPl2", "CPI")

Setting the series names is not necessary but many functions can use the names if they are available. (This overlaps somewhat with S/R dimnames, but is the preferred method in this library as it extends to data which is not a matrix.) The *TSdata* object with elements *input* and *output* is the structure which the functions in this library expect. More details on this structure are available in the help for *TSdata*. The input and output elements can be defined in a number of different ways and new representations can be fairly easily added. For example, when the data is on a remote database as described in the appendix on TS PADI data retrieval, the S/R object is just a description of where the data comes from, rather than the data itself. In this case the *freeze()* function is used automatically by many functions in the DSE library in order to get a copy of the data when calculations are to be performed.

Once data is available a model can be estimated:

model1 <- est.VARX.ls(eg1.DSE.data)
model2 <- est.SS.Mittnik(eg1.DSE.data)

(Note: these models are not the same as those reported in Gilbert,1993. In that paper a variant of est.VARX.ar was used.) The scale of the series in *eg1.DSE.data* are very different, with the result that the covariance matrix of the residuals from the estimation is nearly singular. This is detected during the calculation of residual statistics. Statistics are then calculated using only the non-degenerate subspace and a warning message is printed. A better model might be obtained if the data were scaled differently.

Information about the estimated models can be displayed, for example:

summary(model1)
summary(model2)
model1
model2
stability(model1)
stability(model2)
information.tests(model1, model2).

Typing the name of an object in S/R results in the object being printed. To display plots it is first necessary to open a graphics window:

x11() # in R
motif() # or something else depending on your GUI in Splus

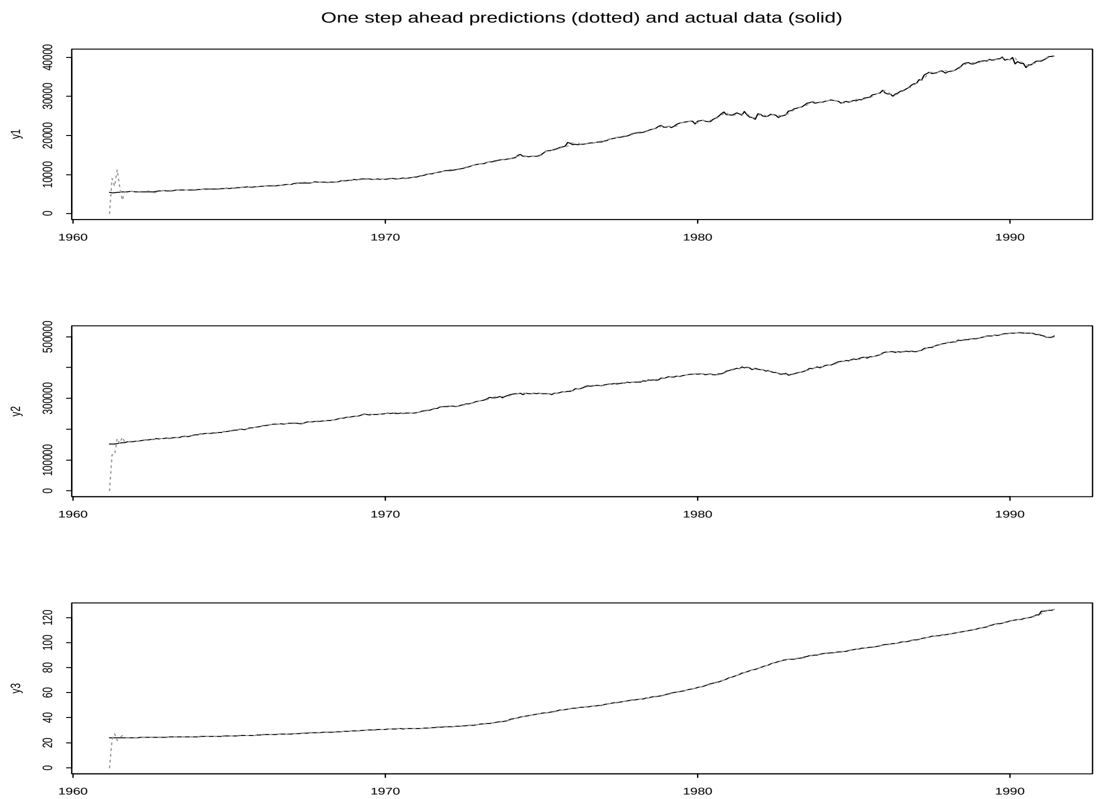
Once a graphics display is active then plots can be viewed:

tfplot(model1)
plot(model1)
tfplot(model2)

tfplot(eg1.DSE.data)
check.residuals(model1)
check.residuals(model2)

The function *tfplot* produces separate graphs for each series while *plot* will put all series on one graph, which may be useful sometimes. You should experiment with both. The first *tfplot* command produces this graphic

:



Note that initial conditions have been set to zero, but the effect of this dies out quickly. (Also note that the graph labels may be slightly different depending on which version DSE and of R or S you are using.)

5. ARMA and State Space TSmodels

Specifying ARMA and SS models is described below, but first their definition is outlined. The linear time-invariant ARMA representation is

$$A(L)\, y_t = B(L)\, \varepsilon_t + C(L)\, u_t$$

where y_t is a p dimensional vector of observed output variables, u_t is an m dimensional vector of input variables, ε_t is a p dimensional unobserved disturbance vector process and

A, *B* and *C* are matrices of the appropriate dimension in the lag (back shift) operator *L*. VAR models can be thought of as a special case of ARMA models with *B(L)=I*. ARIMA models are also a special case of ARMA models.

Note that the time convention here implies that the input variable u_t can influence the output variable y_t in the same time period. This convention is not always used in time-series models but is important for economics data, especially at annual frequencies.

A linear time-invariant state space representation in innovations form is given by

$$z_t = F\, z_{t-1} + G\, u_t + K\, \varepsilon_{t-1}$$

$$y_t = H\, z_t + \varepsilon_t$$

where z_t is the unobserved underlying n dimensional state vector, F is the state transition matrix, G, the input matrix, H, the output matrix, and K, the Kalman gain. The library also has some limited capabilities to work with the more general non-innovations form:

$$z_t = F\, z_{t-1} + G\, u_t + Q\, \nu_t$$

$$y_t = H\, z_t + R\, \varepsilon_t$$

where ν_t is the system noise, Q, the system noise matrix, and R the output (measurement) noise matrix.

Models are specified by setting up the arrays that define the model and grouping them into a *TSmodel* object. Here is an example ARMA model with two series, a second order AR polynomial, a first order MA polynomial and no exogenous variable:

```
AR<- array(c(1, .5, .3, 0, .2, .1, 0, .2, .05, 1, .5, .3) ,c(3,2,2))
MA <- array(c(1, .2, 0, .1, 0, 0, 1, .3), c(2,2,2))
arma <- ARMA(A=AR, B=MA, C=NULL)
rm(AR, MA) # these can be removed from the environment as they are no longer needed
arma
stability(arma)
data.arma.sim <- simulate(arma)
arma <- l(arma, data.arma.sim)
summary(arma)
tfplot(data.arma.sim)
tfplot(arma)
```

Note that arrays are filled in the order of their dimensions, which may not be what you expect. The internal representation of *TSmodel*s may be described in the help for the specific model constructors, but in general it should be considered “opaque” and an understanding of the internal data structure should not be necessary to use the models. The function *l()* evaluates the model with the simulated data. Functions generally use default values for some arguments. For example, the length of the simulation and the covariance of the noise can be specified. The above example uses the default values. See the help on *simulate* for more details. In the example above, *arma* is initially assigned an object of class *TSmodel*, but it is then re-assigned the value returned by *l()*, which is an object of class *TSestModel*. Also, many functions work with different classes of objects, and do different things depending on the class of the argument. The function *tfplot()* works with objects of class *TSdata* and *TSestModel*.

Here is an example of a state space model:

```
f <- array(c(.5, .3, .2, .4), c(2,2)) #beware: do not use capital F=FALSE as a variable name
h <- array(c(1, 0, 0, 1), c(2,2))
k <- array(c(.5, .3, .2, .4), c(2,2))
ss <- SS(F=f, H=h, K=k) # F here is the function argument not a variable name
print(ss)
stability(ss)
data.ss.sim <- simulate(ss)
ss <- l(ss, data.ss.sim)
summary(ss)
tfplot(ss)
```

Data which has been generated with *simulate* is a *TSdata* object and can be used with estimation routines. This provides a convenient way to generate data for estimation algorithms, but remember that estimation will not necessarily get back to the model you start with, since there are equivalent representations (see Gilbert, 1993). However, a good estimate will get close to the likelihood and predictions of the original model.

Here is an example of changing between state space and ARMA representations using the models defined in the previous example:

```
ss.from.arma <- l(to.SS(arma), data.arma.sim)
arma.from.ss <- l(to.ARMA(ss), data.ss.sim)
summary(ss.from.arma)
summary(arma)
summary(arma.from.ss)
summary(ss)
stability(arma)
stability(ss.from.arma)
```

The function *roots()* is used by *stability()* and can be used by itself to return the roots but not evaluate their magnitude[1]. When their arguments are *TSmodels* the functions *to.SS()* and *to.ARMA()* return objects of class *TSmodel* which are not assigned to a variable

1. By default the roots of an ARMA model are calculated by converting the model to state space form, for reasons explained in Gilbert (2000). By specifying *by.poly=T* the method can be changed to use an expansion of the polynomial determinant.

in the above example, but used in the evaluation of *l()*. The models are returned as part of the *TSestModel* returned by *l()*.

6. Model Estimation

The example data *eg1.DSE.data* and *egJofF.1dec93.data*. are available with the DSE library and are used in examples in this section.

To estimate an AR model with the default number of lags:

model.eg1.ls <- est.VARX.ls(trim.na(eg1.DSE.data))

In this example *trim.na* removes *NA* padding from the ends of the data, since the estimation method cannot handle missing values. This padding may not be present, depending on how the data was retrieved.

It is also possible to select a subsample of the data:

subsample.data <- tfwindow(eg1.DSE.data, start=c(1972,1) end=c(1992,12))

This creates a new variable with data starting in January 1972 and ending in December 1992. The S/R function *window* also usually works, however the function *tfwindow* is typically used in the DSE library and this guide because it has occasionally been necessary to correct some problems with *window.* Various functions can be applied to the estimation result:

summary(model.eg1.ls)
print(model.eg1.ls)
tfplot(model.eg1.ls)
tfplot(model.eg1.ls, start=c(1990,1))
check.residuals(model.eg1.ls)

Other estimation techniques are available:

model.eg1.ar <- est.VARX.ar(trim.na(eg1.DSE.data))
model.eg1.ss <- est.SS.from.VARX(trim.na(eg1.DSE.data))
model.eg1.bft <- bft(trim.na(eg1.DSE.data))
model.eg1.mle <- est.max.like(model.eg1.ls) # see note below

Most of these have several optional parameters which control the estimation. Consult the help for the individual functions. *est.max.like* extracts data from a *TSestModel* and uses the model structure and initial parameter values for the estimation. (Note: Maximum likelihood estimation can be very slow and may not converge in the default number of iterations. It also tends to over fit unless used with care, so that out-of-sample performance is not good. I do not generally recommend it, although it does offer possibilities for constraining the structure in specific ways (e.g. fixing some model matrix entries to zero or one). You might consider comparing mle to other estimation techniques using functions discussed in the following sections.)

An important point to note is that the one-step-ahead predictions and related statistics returned by these estimation techniques are calculated by evaluating *l(model, data)* as the final step after the model has been estimated. This can give different results than might be expected using the estimation residuals, particularly with respect to initial condition effects. (For stable models initial condition effects should not be too important. If they are an important factor check the documentation for specific models regarding the specification of initial conditions.)

Also remember when estimating a model that, if you want to predict future values of a variable, it will need to be an output in the *TSdata* object.

For the next example a four variable subset of the data in *egJofF.1dec93.data* will be used. This subset is extracted by

eg4.DSE.data<- egJofF.1dec93.data
output.data(eg4.DSE.data) <- output.data(eg4.DSE.data, series=c(1,2,6,7))

which selects the 1st, 2nd, 6th, and 7th series of the output data. The following uses the currently preferred automatic estimation procedure:

model.eg4.bb <- est.black.box(trim.na(eg4.DSE.data), max.lag=3)

An optional argument *verbose=F* will make the function print much less detail about the steps of the procedure. The optional argument, *max.lag=3,* specifies the maximum lag which should be considered. The default *max.lag=12* may take a very long time for models with several variables. *est.black.box* currently uses *est.black.box*4, also known as *bft(..., standardize=T)* which is called the brute force technique in Gilbert (1995).

The traditional model information criteria tests can be performed to compare models:

information.tests(model.eg1.ar, model.eg1.ss)

An arbitrary number of models can be supplied. The generated table lists several information criteria. For state space models the calculations are done with both the number of parameters (the number of unfixed entries in the model arrays) and the theoretical parameter space dimension. See Gilbert (1993, 1995) for a more extensive discussion of this subject.

Note that converting among representations produces input-output equivalent models, so that predictions, prediction errors, and any statistics calculated from these, will be the same for the models. However, different estimation techniques produce different models with different predictions. So, *est.VARX.ls(data)* and *to.SS(est.VARX.ls(data))* will produce equivalent models and *est.SS.Mittnik(data)* and *to.ARMA(est.SS.Mittnik(data))* will produce equivalent models, but the first two will not be equivalent to the second two.

7. Forecasting

The *TSestModel* object returned by estimation is a *TSmodel* with *TSdata* and some estimation information. To use different data, the new data needs to be in a variable which is a *TSdata* object. For example, suppose a model is estimated by

```
eg4.DSE.model <- est.VARX.ls(eg4.DSE.data)
```

and suppose new data becomes available. If you have direct database access this might be done with something like

```
new.data <- freeze(eg4.DSE.data.names)
```

If database access is not available then for example purposes new.data can be generated with

```
new.data<-TSdata(input=ts(rbind(input.data(eg4.DSE.data),matrix(.1,10,1)),
                          start=start(eg4.DSE.data),
                          frequency=frequency(eg4.DSE.data)),
                 output=ts(rbind(output.data(eg4.DSE.data),matrix(.3,5,4)),
                          start=start(eg4.DSE.data),
                          frequency=frequency(eg4.DSE.data)))
```

This simply appends ten observations of 0.1 onto the input and five observations of 0.3 onto the outputs. The function *ts* assigns time series attributes which are taken from *eg4.DSE.data*. The model can be evaluated with the new data by

```
z <- l(TSmodel(eg4.DSE.model), trim.na(new.data))
```

Recall that *TSmodel()* extracts the *TSmodel* from the *TSestModel*. If database access is available the above can be done in one step:

```
z <- l(TSmodel(eg4.DSE.model), trim.na(freeze(eg4.DSE.data.names)))
```

trim.na on a *TSdata* object removes *NA*s from the ends and truncates both *input* and *output* to the same sub-sample. *l()* does not easily give forecasts beyond the period where all data is available. (Optional arguments can be used to achieve this, but the function *forecast* is more convenient.)

Forecasts are conditioned on *input* so it must be supplied for periods for which forecasts are to be calculated. (That is, *input* is not forecast by the model.) When more data is available for *input* than for *output*, as in *new.data* generated above, then *forecast()* will use *input* data and produce a forecast of *output*.

```
z <- forecast(TSmodel(eg4.DSE.model), new.data)
```

The *input* data can also be specified as a separate argument. For example, the same result will be achieved with

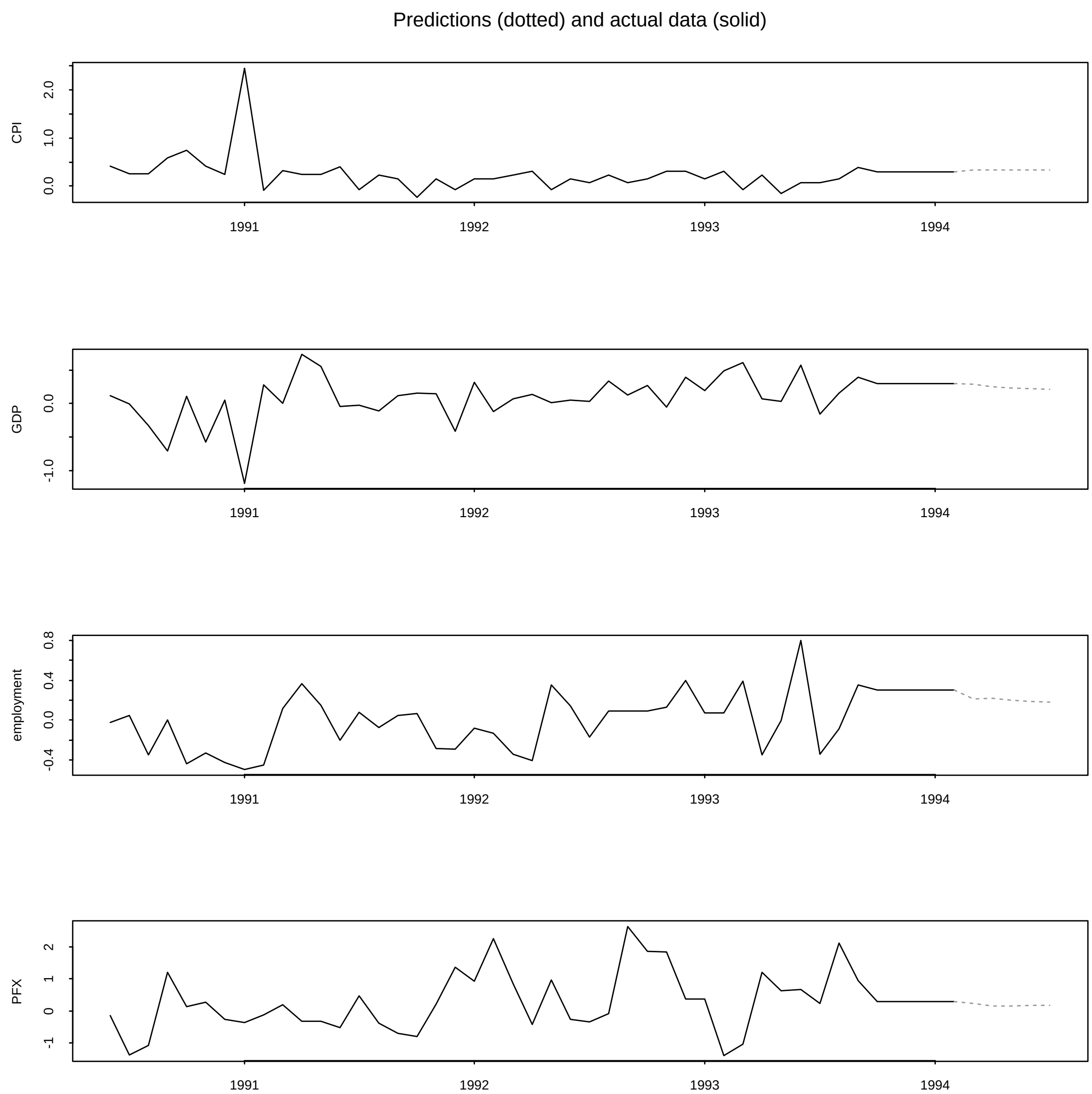
```
z <- forecast(TSmodel(eg4.DSE.model), trim.na(new.data),
         conditioning.inputs=input.data(new.data))
```

The *conditioning.inputs* override *input* in the *TSdata* supplied in the second argument to the function.

To see plots of the forecasts use

tfplot(z, start=c(1990,6))

which produces this result:



Sometimes a forecast for input data comes from another source, perhaps another model. Rather than construct the *conditioning.inputs* as described above, another way to combine this forecast with the historical input data is to use the argument *conditioning.inputs.forecasts*:

z <- forecast(eg4.DSE.model, conditioning.inputs.forecasts=matrix(.5,6,1))

This would use the *input* data from *eg4.DSE.model* and append 6 periods of 0.5 to it.

z <- forecast(TSmodel(eg4.DSE.model), freeze(eg4.DSE.data.names),
conditioning.inputs.forecasts=matrix(.5,6,1))

retrieves new data and appends 6 periods of 0.5 to the input series

Some generic functions which work with the structure returned by forecast:

summary(z)
print(z)
tfplot(z)
tfplot(z, start=c(1990,1))

If you actually want the numbers from the forecast they can be extracted with

forecasts(z)[[1]]

The *[[1]]* indicates the first forecast (in this example there is only one, but the same structures are used for other purposes discussed below. To see a subset of the data use *tfwindow*:

tfwindow(forecasts(z)[[1]], start=c(1994,5))

This prints values starting in the fifth period of 1994.

The horizon for the forecast is determined by the available input data (c*onditioning.inputs* or *conditioning.inputs.forecasts*). If neither of these are supplied then the argument *horizon*, which has a default value of 36, is used to replicate the last period of data to the indicated horizon. For models with no input variables the argument *horizon* controls the length of the forecast.

8. Evaluating Forecasting Models

How well does the model do at forecasting? The first thing to check is that model forecasts actually track the data more or less. The generic function *tfplot*() works with results from the following functions. Recall that the function *l()* applies a *TSmodel* to *TSdata* and returns a *TSestModel* which includes one-step ahead forecasts. It can be used with any *TSmodel* and *TSdata* of corresponding dimension. So

z <- l(TSmodel(eg4.DSE.model), new.data)

applies the previously estimated model to the new data, and

tfplot(z)

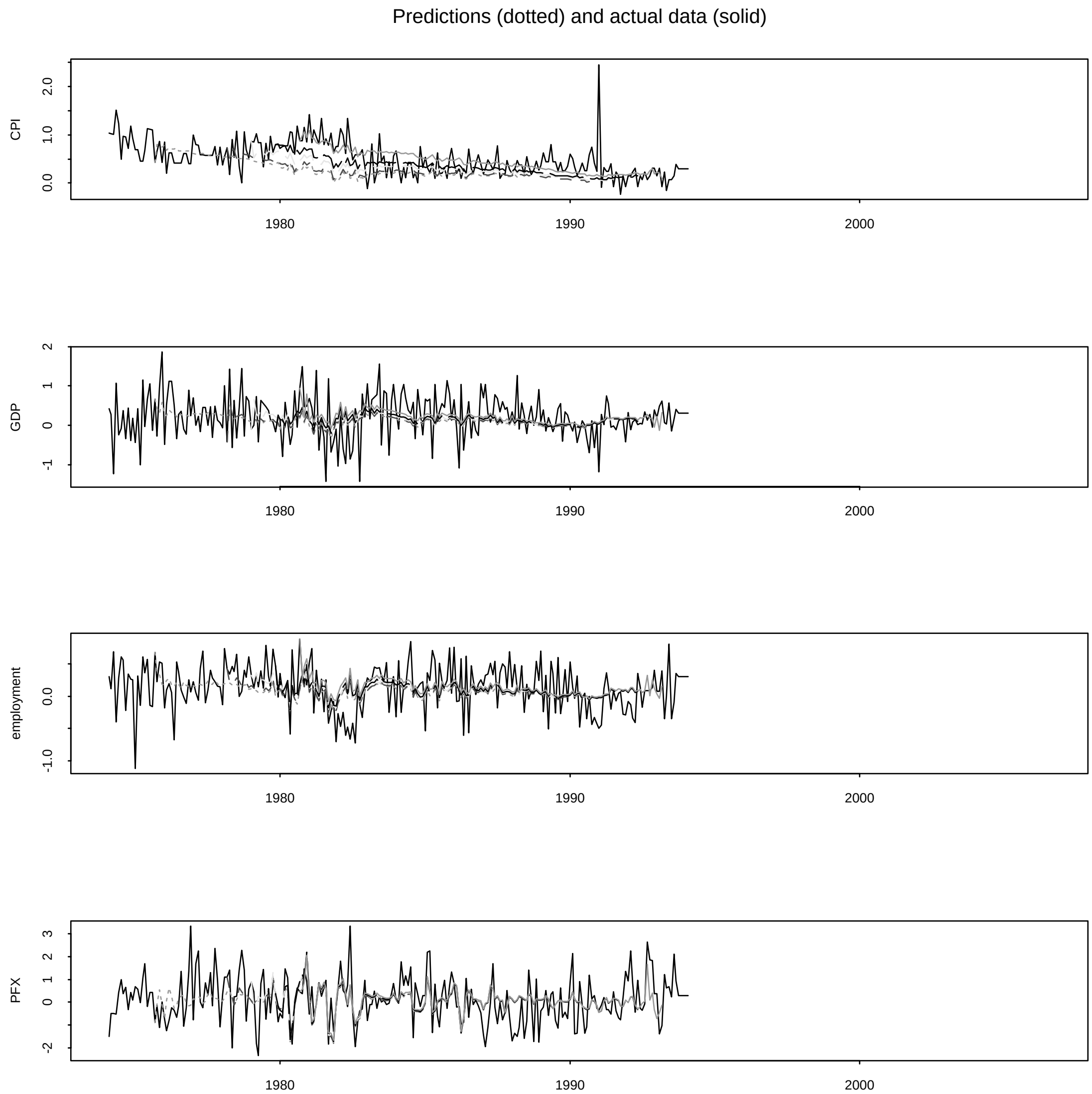
would plot the one-step ahead forecasts. The function *forecast* discussed in the previous section calculates multi-step ahead forecasts from the end of the data. For evaluating forecasting models it is more useful to calculate forecasts within the sample of available data. This is for two reasons. First, the forecast can be compared against the actual outcome. Second, if the model has an *input* then the forecast is conditioned on it. If data is available then the actual *input* data can be used. (But beware that this is not a true test of the model's ability to forecast if the whole sample has been used to estimate the model.) There are two methods to calculate multi-step ahead forecasts within the data sample. *featherForecasts* produces multiple period ahead forecasts beginning at specified periods. The name comes from the fact that the graph sometimes looks like a feather (although it will not if the forecasts are good).

```
z <- featherForecasts(TSmodel(eg4.DSE.model), new.data)
tfplot(z)
```

In the example above the forecasts begin by default every tenth period. In the following example the forecasts begin at periods 20, 50, 60, 70 and 80 and forecast for 150 periods.

```
z <- featherForecasts(TSmodel(eg4.DSE.model), new.data,
            from.periods =c(20, 50, 60, 70, 80), horizon=150)
tfplot(z)
```

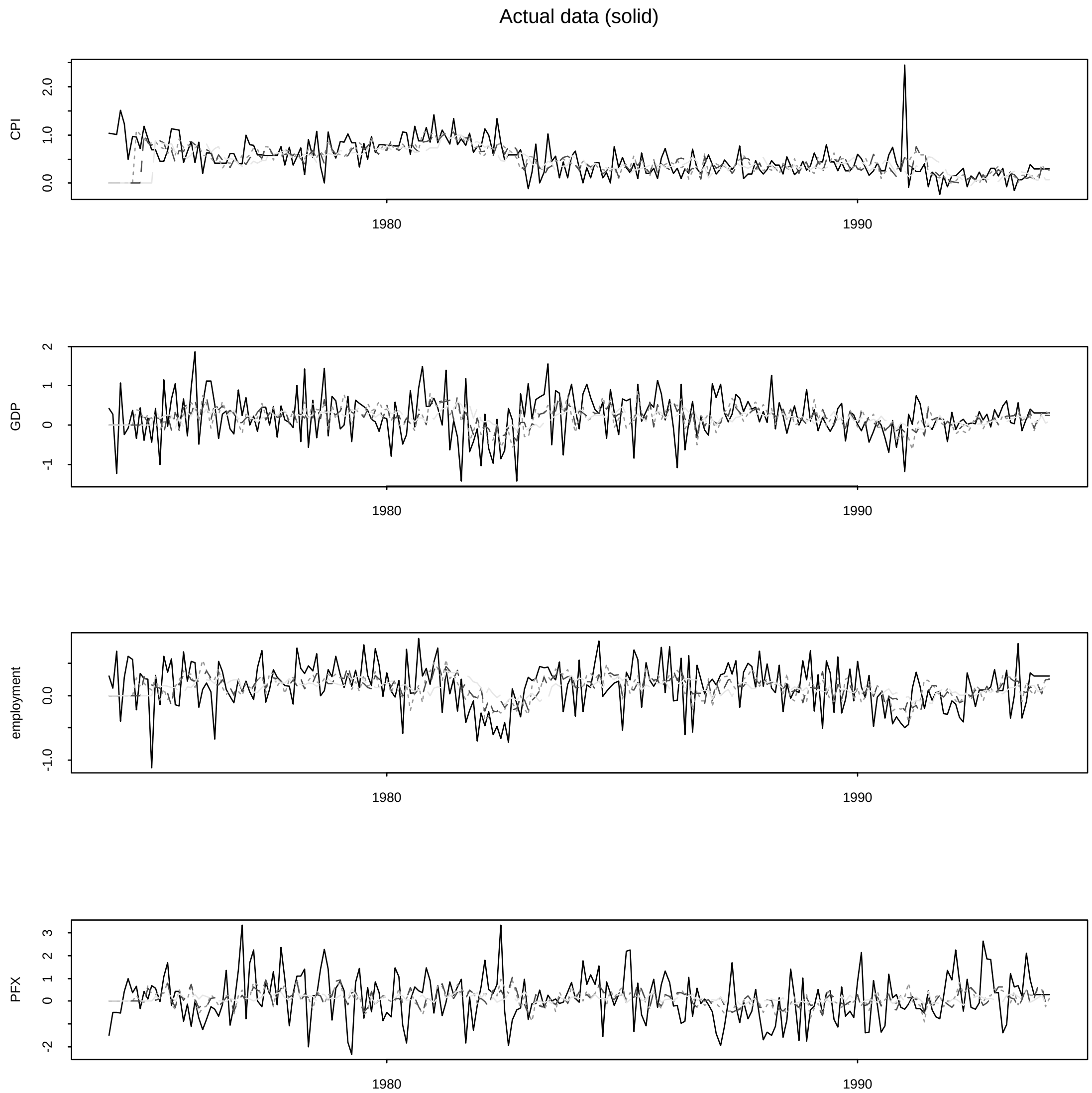
The plot looks like this:



The second method, *horizonForecasts*, produces forecasts from every period for specified horizons.

z <- horizonForecasts(TSmodel(eg4.DSE.model), new.data, horizons=c(1,3,6))
tfplot(z)

produces forecasts 1, 3 and 6 steps ahead. The plot looks like this:



The result is aligned so that the forecast for a particular period is plotted against the actual outcome for that period. Thus, in the last example, the plot will show the data for each period along with the forecast produced from 1, 3, and 6 periods prior. This plot is particularly useful for illustrating when models do well and when they do not. A common experience with economic data is that models do well during periods of expansion and contraction, but miss the turning points. The forecast covariance, to be discussed next, averages over all periods. It is quite possible that a model can indicate turning points well but not do so well on average, and thus be overlooked if only forecast covariance is considered. It is always useful to keep in mind the intended use of the model.

The numbers which generate the above plot can be extracted from the result of *horizonForecasts* with *forecasts()*. This gives an array with the first dimension corresponding to the horizons and the time frame aligned to correspond to the data. So *forecasts(z)[2,30,]* from the above example will be the prediction made for the 30th period from 3 periods previous (the second element indicated in *horizons* is 3) and *forecasts(z)[3,30,]* will be the prediction made for the 30th period from 6 periods previous (*horizons[3]* is 6). Remember that these forecasts are conditioned on the supplied input data, which means that the output variables here are forecast 1, 3 and 6 periods ahead, but true, not forecasted, input data is used.

If the forecasts look reasonable then examine the forecast errors more systematically. The following calculates the forecast covariances at different horizons.

```
fc <- forecastCov(TSmodel(eg4.DSE.model), data=eg4.DSE.data)
tfplot(fc)
tfplot(forecastCov(TSmodel(eg4.DSE.model), data=eg4.DSE.data, horizons= 1:4))
```

The last example calculates for horizons from 1 to 4 rather than the default 1 to 12. To see how the model forecasts relative to a zero forecast and a trend forecast:

```
fc <- forecastCov(TSmodel(eg4.DSE.model), data=eg4.DSE.data, zero=T, trend=T)
tfplot(fc)
```

This is a very useful check (and often very humbling).

You can also get out-of-sample forecast covariances. This will be discussed in the next section.

There is not yet implemented in DSE any measure of forecast errors which can be compared across models - inevitably the covariance of the error is smaller for less variable series and is also affected by scaling of the series. This may just mean that the series is easier to predict or has a different scale, not that the forecast equation is more brilliant. MAPE may be implemented sometime.

9. Evaluating Estimation Methods

One way to test estimation techniques is to specify a “true” model which is used to produce simulated data and then examine how well an estimation technique finds the true model. This is not as general as theoretical results, since it is really only valid at the “true” parameter values and for the sample size tested, however, it can be illustrative and theoretical results for small samples are very difficult to obtain. It also provides a very good cross check of the simulation and estimation code. Also, equivalent representations may have effects which are not yet fully appreciated in the theoretical literature. The following models from Gilbert (1995) will be used to illustrate.

```
 mod1 <- ARMA(A=array(c(1,-.25,-.05), c(3,1,1)), B=array(1,c(1,1,1)))
mod2 <- ARMA(A=array(c(1,-.8, -.2 ), c(3,1,1)), B=array(1,c(1,1,1)))
 mod3 <- ARMA(
     A=array(c(
             1.00,-0.06,0.15,-0.03,0.00,0.02,0.03,-0.02,0.00,-0.02,-0.03,-0.02,
```

```
            0.00,-0.07,-0.05,0.12,1.00,0.20,-0.03,-0.11,0.00,-0.07,-0.03,0.08,
            0.00,-0.40,-0.05,-0.66,0.00,0.00,0.17,-0.18,1.00,-0.11,-0.24,-0.09 )
            ,c(4,3,3)),
    B=array(diag(1,3),c(1,3,3)))
```

mod2 has a unit root, as can be verified with *roots(mod2)* or *stability(mod2)*.

The function *MonteCarloSimulations* runs *simulate* repeatedly to give many data samples.

```
z <-  MonteCarloSimulations(mod1, sampleT=100)
tfplot(z)
distribution(z)
```

Usually it is not necessary to use *MonteCarloSimulations* and actually save all the simulations since the seed and other information about the random number generator (RNG) can be used to reproduce the samples. Thus functions for testing estimation methods can produce the same samples when they are needed.

The function *EstEval* simulates and then estimates models:

```
e.ls.mod1 <- EstEval( mod1, replications=100,
    simulation.args=list(sampleT=100, sd=1),
    estimation=”est.VARX.ls”, estimation.args=list(max.lag=2),
    criterion=”TSmodel”,
    rng=list(kind="default", normal.kind="default",
            seed=c(13,44,1,25,56,0,6,33,22,13,13,0) ) ) # Splus seed - see below
```

In this example simulation and estimation will be repeated 100 times with samples of size 100 and the standard deviation of the model noise will be set to 1. *simulation.args* are passed to the function *simulate*, which may take different arguments depending on the class of the model. Estimation is done with the function *est.VARX.ls* and *estimation.args* are passed to it. The argument *criterion* specifies what should be returned from the estimation. In this case the model is returned (An object of class *TSmodel*) but not additional information as is usually returned in the object *TSestModel*. It is also possible to specify *coef* or *roots* to return only that specific information, but that information can be extracted from the *TSmodel* as illustrated below. In general *EstEval* will work with any estimation method which will take the results of *simulate* applied to the supplied model and returns something that *criterion* can extract. That is, if criterion*(*estimation*(simulate(*model*)))* returns something (with criterion and estimation replaced by the functions you supply and model replaced by the model you supply), then *EstEval* should work with your functions. This does not mean that plots described below will necessarily work or make sense.

The argument *rng* is optional here and in all the examples below. If supplied, the RNG and seed will be set. This is useful if an experiment is to be reproduced. Using Splus 3.2 and 3.3 the settings indicated in this section will reproduce the results in Gilbert (1995). It is possible to generate similar random experiments in S and in R, but not using the Splus default generator. If the argument *rng* above is given as

rng=list(kind="Wichmann-Hill", seed=c(979,1479,1542), normal.kind="Box-Muller")

then the uniform RNG is set to Wichmann-Hill, the normal transformation is set to Box-Muller, and the initial seed is set. With the RNG set in this way both Splus and R will produce similar results. These settings are reset to their previous values when the function completes. They can be set so that they do not revert using the function

set.RNG(kind="Wichmann-Hill", seed=c(979,1479,1542), normal.kind="Box-Muller")

The argument *seed* is optional (and other values can be supplied but they should be consistent with the generator). An initial seed will be generated if it is omitted.

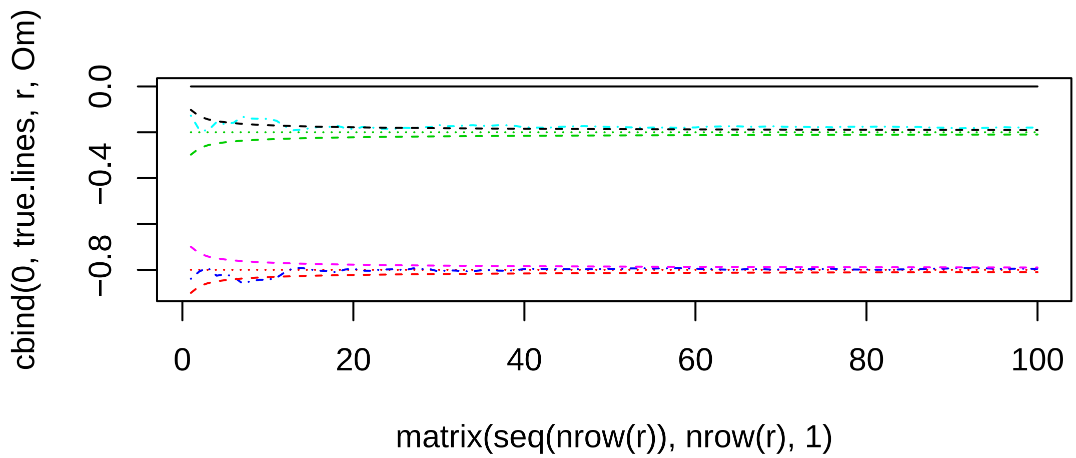
The following uses *mod2* as the true model.

```
e.ls.mod2 <- EstEval( mod2, replications=100,
    simulation.args=list(sampleT=100, sd=1),
    estimation="est.VARX.ls", estimation.args=list(max.lag=2),
    criterion="TSmodel",
#   rng=list(kind="default", normal.kind="default",
#           seed=c(13,43,7,57,62,3,30,29,24,54,47,2) ) #Splus seed
    )
```

To plot a line chart of the cumulative average of the estimated parameters use *coef* to extract the parameters (coefficients) from the *TSmodel*:

```
par(mfcol=c(2,1)) # set the number of plots on the graphics device
tfplot(coef(e.ls.mod1))
tfplot(coef(e.ls.mod2))
```

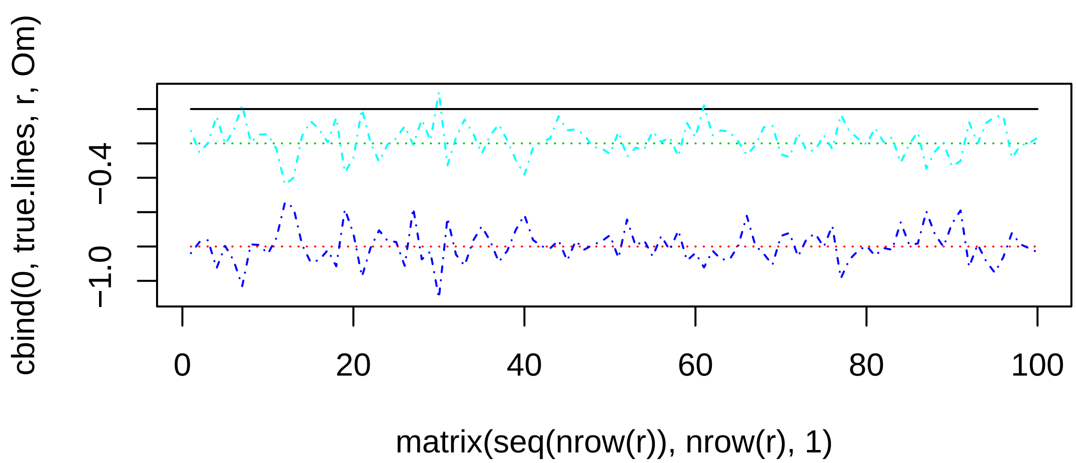
The second plot looks like this:



The straight line indicates the true value. To plot a line chart of the estimated parameters use *coef* to extract the parameters from the TSmodel:

par(mfcol=c(2,1)) # set the number of plots on the graphics device
tfplot(coef(e.ls.mod1), cum=F, bounds=F)
tfplot(coef(e.ls.mod2), cum=F, bounds=F)

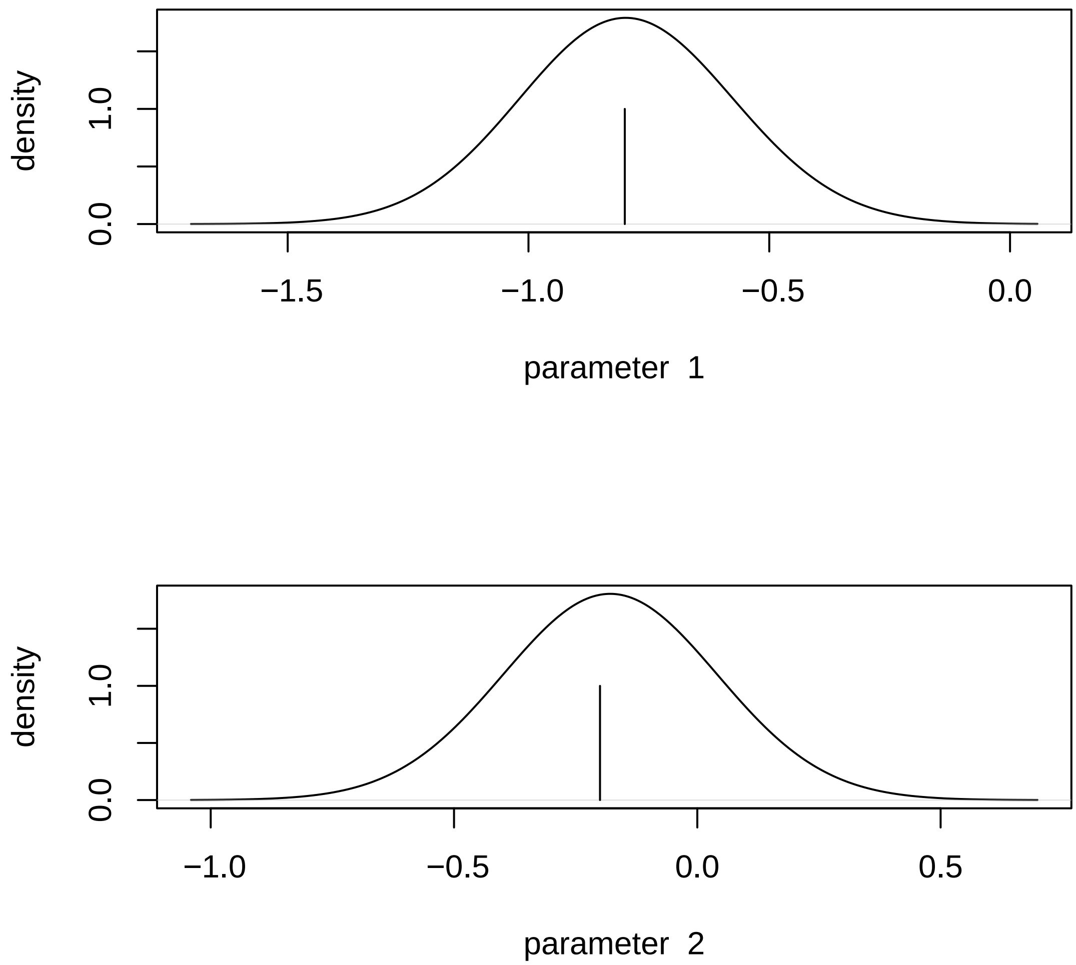
bounds controls whether or not estimated one standard deviation bounds are plotted. The second plot looks like this:



To plot the distribution of estimates:

distribution(coef(e.ls.mod1), bandwidth=.2) *distribution(coef(e.ls.mod2), bandwidth=.2)*

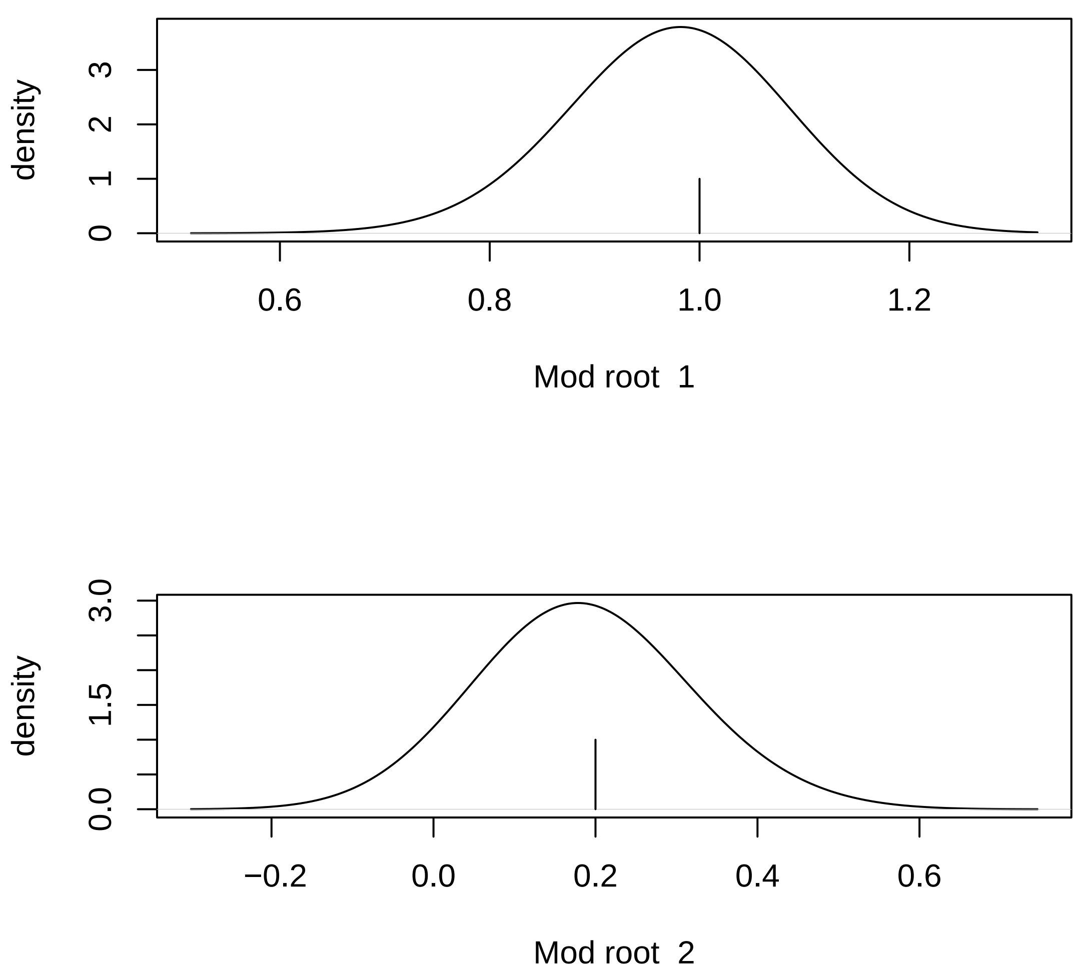
The second plot looks like this:



To plot the roots of the estimated model use *roots* to extract the roots from the *TSmodel*:

e.ls.mod1.roots <- roots(e.ls.mod1)
plot(e.ls.mod1.roots)
plot(e.ls.mod1.roots, complex.plane=F)
plot(roots(e.ls.mod2), complex.plane=F)
distribution(e.ls.mod1.roots, bandwidth=.2)
distribution(roots(e.ls.mod2), bandwidth=.1)

bandwidth is an argument passed to the kernel estimator used to generate the plot. The last plot looks like this:



Some attention to the equivalence of different model representations is necessary when evaluating estimation methods. For example, if the state space equivalent of a VAR model is used as the true model for simulation and *est.VARX.ls* is used for estimation then parameter estimates will be very different from those of the state space model (but root estimates should still be similar). Many estimation techniques may also do some model selection (such as *est.black.box* does), so the returned models may have different numbers of parameters and/or lags.

Evaluating models based on their forecast performance avoids some of these difficulties. In any case, since forecasting is often the end objective, it is useful to evaluate models directly on their forecasting performance. The function *forecastCov.estimatorsWRTtrue()* evaluates estimation methods using a given true model for simulation. It calculates the covariance of forecast errors of the estimated models relative to the output of the true model:

```
pc <- forecastCov.estimatorsWRTtrue(mod3,
     estimation.methods=list(est.VARX.ls=list(max.lag=6)),
     est.replications=2, pred.replications=10,
     trend=F, zero=F,
     rng=list(kind="default", normal.kind="default",
             seed=c( 53,41,26,39,10,1,19,25,56,32,28,3) ) ) #Splus seed
```

The names of the elements in the list *estimation.methods* specify the estimation methods and their value is a list of the arguments to the method. If no arguments are required then the value should be specified as *NULL*. Optional arguments *trend* and *zero* indicate if the covariance for forecasts of zero and a simple trend should also be calculated. These are useful benchmarks. *est.replications* controls the number of times a sample is generated and used for estimating a model with each estimation method. *pred.replications* controls how many times the forecasts from the estimated model are compared with output from the true model. Thus the total number of simulations is *est.replications* + *est.replications* * *pred.replications*, so 22 in the above example.

A similar function is available which applies a model reduction procedure after the estimation:

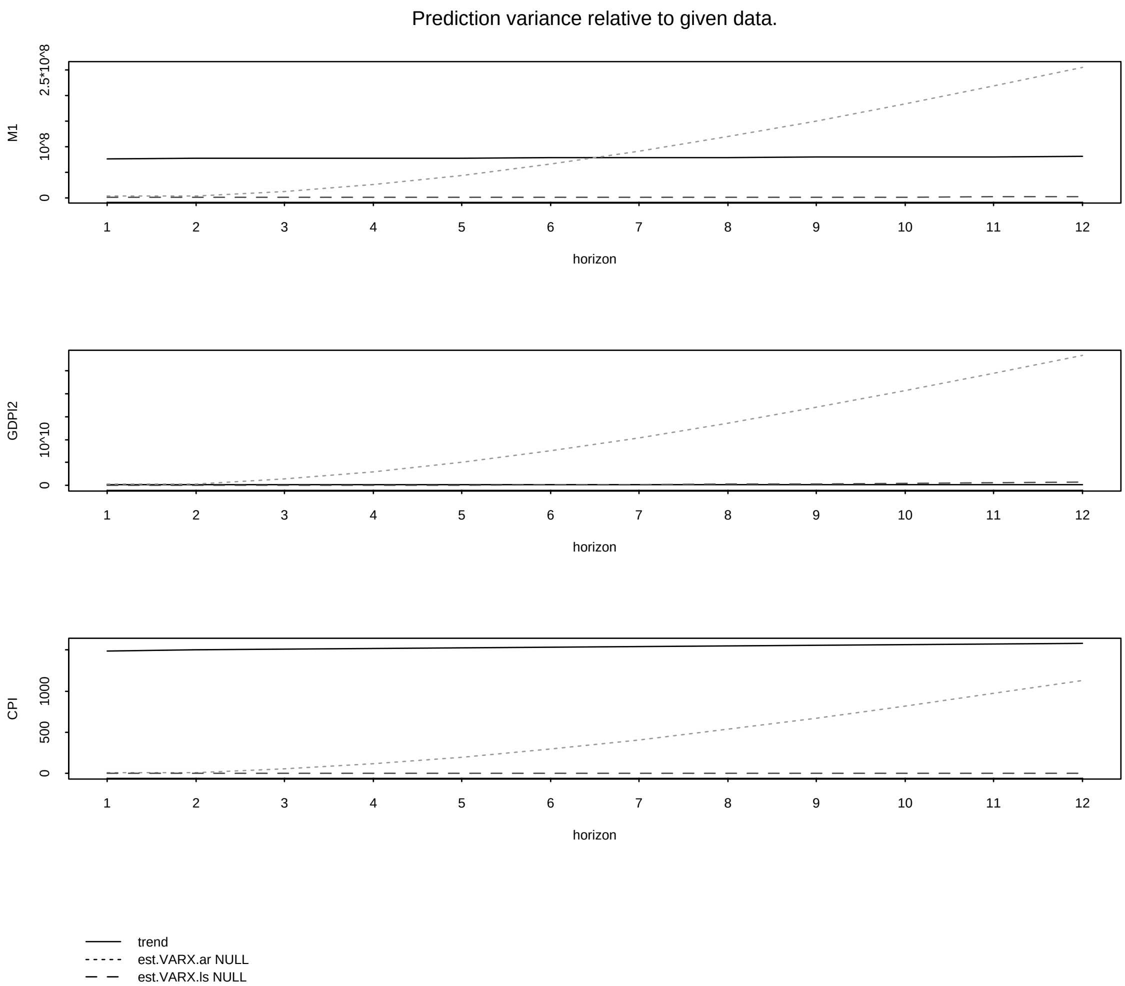
```
pc.rd <- forecastCov.reductionsWRTtrue(mod3,
     estimation.methods=list(est.VARX.ls=list(max.lag=3)),
     est.replications=2, pred.replications=10,
     rng = list(kind = "default", normal.kind="default",
             seed=c(29,55,47,18,33,1,15,15,34,46,13,2) ) )
```

The reduction procedure used is *reduced.models.Mittnik.* An optional argument *criteria* can be specified. This controls the model selection criteria used by the reduction technique.

It is possible to compare different estimation techniques on the basis of their out-of-sample forecasting error with respect to a data sample. In the following example *estimation.sample* controls the portion of the sample used for estimation. It can be a fraction indicating a portion of the sample, or it can be an integer in which case it will be treated as the number of periods to use for estimation.

```
z <-out.of.sample.forecastCov.estimatorsWRTdata(trim.na(eg1.DSE.data),
     estimation.sample=.5,
     estimation.methods = list(est.VARX.ar=NULL, est.VARX.ls=NULL),
     trend=T)
tfplot(z)
```

The plot looks like this:



In the example below the number of lags is limited (the default is 12 for *est.black.box4*) and printing of intermediate results is suppressed.

```
z <-out.of.sample.forecastCov.estimatorsWRTdata(trim.na(eg1.DSE.data),
    estimation.sample=.5,
    estimation.methods = list(
            est.black.box4=list(max.lag=3, verbose=F),
            est.VARX.ls=list(max.lag=3)),
    trend=T, zero=T)
tfplot(z)
```

The object returned by *out.of.sample.forecastCov.estimatorsWRTdata()* contains the estimated models so it is possible to extract the models and use *l*, *horizonForecasts* and *featherForecasts*. In the above example the model estimated with *est.black.box4* is the first model and that estimated with *est.VARX.ls* is the second, so *zz <- horizonForecasts(TSmodel(z, select=1) , TSdata(z), horizons=c(1,3,6))*

would generate an object with the actual forecasts for the model estimated with *est.black.box4* (rather than the covariance of the forecast errors) and *forecasts(zz)[3,30,]* will then be the prediction made for the 30th period from 6 (the third element of *horizons*) periods previous. The generic function *horizonForecasts()* can also be applied directly to *z* and the appropriate information will be extracted to generate forecasts for all the estimated models.

10. Adding New TSdata Classes

Data used by functions in this library are objects of class *TSdata*. The default methods assume that this is a list with an element *output* and optionally an element *input*, each of which is a (multivariate) time series object. New classes of time series can be defined and the DSE library should work as long as the methods describe in the *tframe* library are implemented for the new time series class. This usually will not require any changes to *TSdata* methods (or anything else in the DSE library). The time series class *tfPADIdata* defined in the *tframe* library is an object which does not contain data, but only a description of where to get the data. The generic function *freeze()* calls *freeze.tfPADIdata()* which uses the location descriptor in order to get a fixed copy of the data as a time series matrix.

More generally, it is possible to define new specific classes of *TSdata*. The *TSPADIdata* object described in the appendix on database interfaces is an object of class *TSdata* and specific class *TSPADIdata*. The *input* and *output* for this class are time series location descriptors of class *tfPADIdata*. Many functions in this library require matrices for *input* and *output* in order to do calculations. In this case they use the function *freeze()* before doing any calculations. The method *freeze.TSPADIdata()* uses *freeze.tfPADIdata()* on each element.

11. Adding New TSmodel Classes

Models used in the library are of class *"TSmodel"* with secondary classes to indicate specific types of models. The original library supported subclass *"ARMA"* and *"SS"*. The current version also support subclass *"troll"*. (*** The interface for running troll models is broken at present. Another, more easily available example is under construction) To run models in this subclass requires the Troll software from Intex Solutions, Inc. It also requires the TSPADI interface. The main methods which will be necessary for a new class of models "*xxx*" are *print.xxx, is.xxx, l.xxx, simulate.xxx, seriesNamesInput.xxx, seriesNamesOutput.xxx, check.consistent.dimensions.xxx*, and *MonteCarloSimulations.xxx*. Also, the method *to.xxx* is useful for converting models from existing classes to this new class where possible. Models should inherit from *TSmodel*.

The *troll* class of models is fairly interesting from a programming perspective, since the data is not native to S/R and the models are not run within S/R. One reason for wanting to do this is to use all of the other tools in the library to analyze models which have already been built and are running in other environments. Troll has very good algorithms for running "forward looking models" which are currently popular in economics. The tools in the DSE library (e.g. functions for analyzing forecasting properties) can be used as if the troll models were run directly in S/R, even though they are actually run with completely separate software.

The *troll TSmodels* provide an example of how to implement additional classes of models.

12. Curvature Calculations

13. Juice Functions

14. Cookbook for Monitoring Models

This section gives a brief recipe for building short term forecasting models. It is intended to be self-contained although there are references to other sections for additional information. The function described in this section are made available in R by:

library("padi") #for database interface.
library("dsepadi") #for the dse layer on top of database interface.
library("monitor") #for monitoring model functions.

The term "monitoring" comes from the fact that one is often trying to monitor the current state of the economy based on data from prior periods, since there is typically some lag before statistical agencies release data for the current period. The steps, explained in more detail below, are:

1/ specify the data series to use in the model

2/ estimate a model and confirm that it is reasonable

3/ repeat 1 and 2 if other series are to be considered for competing models (beware that fishing can be dangerous)

4/ run the monitoring program to produce forecasts

and optionally

5/ set up an automatic program to run the monitoring program and distribute results

This library use the TS PADI interface explained in more detail in an appendix. For example purposes it is assumed that the data can be retrieved from an “economic time series” (ets) server. The examples use names of series which are used internally at the Bank of Canada and are probably not available elsewhere. Start S/R and open a graphics window with

motif() # or something else in Splus

or

x11() # in R

If running remotely it may be necessary to use an argument like *"-display YourWorkstation:0.0"* to display on your workstation. A few more details on running S/R are given in Section 2 of this guide.

Step 1- specify the data

The data is specified in an variable which indicates the name of the series, the source, any transformations which should be applied, and possibly some other options. For more details see the appendix. An example of a model which contains two outputs and no inputs is

```
cbps.manuf.data2.ids <- TSPADIdata2(
    output=list(c("ets", "", "i37013","percent.change","cbps.prod."),
            c("ets", "", "i37005","percent.change","manuf.prod.")),
    pad.start=F,
    pad.end =T )
```

With the above, the data will be converted to percent change when it is read from the database. The default behaviour for data retrieval is to trim all series to the same length. The length is such that there are no missing values on the ends. *pad.start* and *pad.end* can be used to modify this behaviour. With *pad.end=T* all series are padded on the end with *NA*s to give a length which will include the most recent data value from any series. This is preferred for forecasting but the *NA*s have to be trimmed with *trim.na* for estimation procedures. The data is actually retrieved from the database with

```
cbps.manuf.data2 <- freeze(cbps.manuf.data2.ids)
```

The following example specifies one input series and one output series. It uses an alternate constructor (*TSPADIdata* vs. *TSPADIdata2*) which takes arguments in a different format. (The result is the same but different styles sometimes seem more convenient.)

```
manuf.data.ids <- TSPADIdata(
    input ="lfsa455", input.transforms="percent.change",
    input.names="manuf.emp.",
    output="I37005", output.transforms="percent.change",
```

```
    output.names="manuf.prod.",
    server="ets", pad.start=F, pad.end =T  )
manuf.data <- freeze(manuf.data.ids)
```

The data can be plotted with

```
tfplot(manuf.data)
```

In this example the plot shows missing data in the middle. In this somewhat unusual case it is necessary to trim the beginning of the data set to remove the portion up to the end of the missing data. This could be done with

```
manuf.data <- tfwindow(manuf.data, start=c(1976,2))
```

However, the trimming would have to be repeated each time the data is updated from the database, which is especially inconvenient for automatic procedures described further below. A better way is to set the starting period for retrieved data with

```
manuf.data.ids <- modify.TSPADIdata(manuf.data.ids, start=c(1976,2))
```

then when data is retrieved with

```
manuf.data <- freeze(manuf.data.ids)
```

it will start after the missing data. The start can also be specified with the argument *start* for the function *TSPADIdata*.

A more detailed plot of the last portion of the data can be produced with

```
tfplot(manuf.data, start.=c(1995,11))
```

Note the "." after start is part of the name of the argument. It is often not necessary since truncated arguments usually match without problem, but is required in the case of tfplot so that the argument is not confused with the function start. To specify and retrieve data with two input series and one output series

```
cbps.manuf.data.ids <- TSPADIdata(
    input =c("lfsa462","lfsa455"), input.transforms="percent.change",
    input.names=c("cbps.emp.", "manuf.emp"),
    output="i37013", output.transforms="percent.change",
    output.names="cbps.prod.",
    start=c(1976,2),
    server="ets", db="", pad.start=F,  pad.end =T  )
cbps.manuf.data <- freeze(cbps.manuf.data.ids)
```

To specify and retrieve data with one input variable and two output variable

```
cbps.manuf.data3.ids <- TSPADIdata(
    input ="lfsa462",
    input.transforms="percent.change",input.names="cbps.emp.",
    output=c("i37013", "i37005"),
```

```
    output.transforms=c("percent.change", "percent.change"),
    output.names=c("cbps.prod.","manuf.prod."),
    start=c(1976,2),
    server="ets", db ="", pad.start=F, pad.end =T)
cbps.manuf.data3 <- freeze(cbps.manuf.data3.ids)
```

Setting *start* is only necessary because of this rather unusual case were there are missing values in the middle of one series

Step 2 - estimate model

At this point it may be useful to make S/R prompt for a return before each new graph is produced. This is done with

```
dev.ask(T)
```

A model can be estimated with various estimation techniques, some of which are described in Section 6. For example:

```
manuf.model  <- bft(trim.na(manuf.data))
```

This uses a “brute force technique” described in Gilbert (1995). It might take some time to run. It uses a default maximum number of lags of 12. The estimation is faster if a smaller number of lags is specified using

```
manuf.model  <- bft(trim.na(manuf.data), max.lag=5)
```

By default the bft procedure prints information as it proceeds. This can be stopped using

```
manuf.model  <- bft(trim.na(manuf.data), verbose=F, max.lag=5)
```

To display the parameters of the estimated model just type the name of the variable in which it was stored:

```
manuf.model
```

and to plot it:

```
tfplot(manuf.model)
tfplot(manuf.model, start=c(1990,1))
tfplot(manuf.model, start=c(1995,1))
```

Models for the other specified data sets can be estimated in the same way:

```
cbps.manuf.model <- bft(trim.na(cbps.manuf.data),verbose=F)
tfplot(cbps.manuf.model)
tfplot(cbps.manuf.model, start=c(1995,1))
```

To forecast with the model using all available data

```
z <- forecast(TSmodel(manuf.model), trim.na(manuf.data),
    conditioning.inputs=input.data(manuf.data))
```

```
tfplot(z, start=c(1995,1))
```

To see the forecast use

```
forecasts(z)[[1]]
tfwindow(forecasts(z)[[1]], start=c(1996,3))
```

Forecasting is discussed in Section 7.

To evaluate how well the model does at forecasting, look at the covariance of the forecast error at different horizons with

```
fc <- forecastCov(manuf.model)
tfplot(fc)
```

It is also good to consider how well the forecast does relative to a zero and a trend forecast:

```
fc <- forecastCov(manuf.model,  zero=T, trend=T)
tfplot(fc)
```

The above forecast error analysis is done within the sample which was used for estimating the model. An out-of-sample forecast error analysis is typically a better indication of how well the model will really do. This can be done by using *tfwindow* to truncate the data to a subset for estimation and then evaluate the forecast error on the remainder. Another compromise, which is attractive when short data sets are involved, is to do an out-of-sample evaluation of the performance of an estimation procedure, and then hope that the procedure will continue to estimate good models when the whole data set is used.

```
outfc <-out.of.sample.forecastCov.estimatorsWRTdata(trim.na(manuf.data),
    estimation.sample=.5,
    estimation.methods = list(bft=list(verbose=F), est.VARX.ls=NULL),
    trend=T, zero=T)
tfplot(outfc)
```

The *bft* procedure is generally fairly good but it can sometimes be out performed by a simple least squares estimation, especially for univariate models. Its real strength is for multivariate models:

```
outfc <-out.of.sample.forecastCov.estimatorsWRTdata(
   trim.na(cbps.manuf.data3),
   estimation.sample=.5,
   estimation.methods = list(bft=list(verbose=F), est.VARX.ls=NULL),
   trend=T, zero=T)
tfplot(outfc)
```

More details are given in Section 8.

Once a model has been chosen it can be re-used, rather than re-estimating each time there is a new data point. This is done by extracting the model from the object returned by the estimation procedure. This object is a model with data and some estimation information. If you want to use different data then the data needs to be retrieved again using the variable which indicates the source. For example

```
new.data <- freeze(manuf.data.ids)
```

To run the model and get one-step-ahead predictions with the new data use

```
z <- l(TSmodel(manuf.model), trim.na(new.data))
```

Or the data retrieval can be done in the same step with

```
z <- l(TSmodel(manuf.model), trim.na(tfwindow(freeze(manuf.data.ids),
    start=c(1976,2))))
tfplot(z)
tfplot(z, start=c(1995,8))
```

Forecasts more than one-step-ahead require input series up to the horizon for which the forecast is to be produced. To run the model and get forecasts when more input than output data is available:

```
z <- forecast(TSmodel(manuf.model), trim.na(new.data),
    conditioning.inputs=trim.na(input.data(new.data)))
tfplot(z, start=c(1995,6))
```

The effect of this is to trim *NA*s from *input* separately from *output* so that *input* will not be truncated to the same ending period as *output*. If you actually want the numbers rather than plots of the data use

```
forecasts(z)[[1]]
```

or

```
tfwindow(forecasts(z)[[1]], start=c(1996,2))
```

will print values starting in the second period of 1996.

The horizon for a model with no inputs is determined by the argument *horizon*, which has a default value of 36. For a model which requires input (conditioning) data, the horizon for the forecast is determined by the input data, *conditioning.inputs* or *conditioning.inputs.forecasts*. If none of these are supplied then the argument *horizon* is used to replicate the last period of input data to the indicated horizon.

At the Bank of Canada PADI is an interface to a Fame server. The forecast data can be put into a Fame database with

```
putpadi(forecasts(z)[[1]], dbname="nameofdatabase.db",
    series=seriesNamesOutput(z))
```

In the above

seriesNamesOutput(z)

extracts a character vector of the series names.

Step 3 - reconsider the data and model

The performance of alternative models on a given data set can be compared by looking at the forecast error covariance from *forecastCov.* Repeat the required parts of steps one and two and choose the model which does best at the horizons of interest. Sometimes the real purpose of a monitoring model is just to forecast one series (the series of primary interest). Other series are included only because they provide additional information for forecasting the series of primary interest. One disadvantage of including additional series is that it increases the number of parameters which must be estimated, and thus reduces the quality of the estimates. At this step you should reconsider what series are included for the model. Choose the model which does best on the series of primary interest (but see also "Juice Functions").

Step 4 - run the monitoring

During the S session, variables (e.g. models and data) are saved in a subdirectory .Data below the directory where you started S. (In R they are in the file .RData.) The variables will be available the next time S/R is started from the same subdirectory. One danger is that you can overwrite an existing variable just by assigning a new value to the name. Once you have a model to use for forecasting it is a good idea to save it in a separate file so it will not be lost by accident. The model *manuf.model* and the corresponding data identifiers can be saved in the file "manuf.model.definition" with

dump(c("manuf.model","manuf.data.ids"), fileout="manuf.model.definition")

If necessary they can then be retrieved with

source("manuf.model.definition")

The model can be run to produce a forecast and mail the results to a list of recipients. The function to do this compares the current data to a previous copy of the data in order to determine if an updated forecast should be run. The comparison data is first initialized with

manuf.previous.data <- freeze(manuf.data.ids)

then in order to make the data look like it has changed

output.data(manuf.previous.data)[1,1] <- NA

and to run the forecast and E-mail the results

r <-simple.monitoring(manuf.model, manuf.data.ids, manuf.previous.data,
mail.list="pgilbert@bank-banque-canada.ca",

```
message.title="    Manufacturing Monitoring  ",
message.subject="Manufacturing Monitoring",
show.start= c(0,-3),
report.variables=seriesNames(manuf.data.ids),
data.sub.heading="   %chg       %chg",
message.footnote="             f - forecast value" ,
data.tag=" ",
forecast.tag="f" )
```

The status of the result can be checked with

r$status

and the comparison data should also be updated with

manuf.previous.data <- r$data

Especially for debugging purposes it is often useful to keep a more complete record of the data and model used to produce the forecast This can be done with the *simple.monitoring* argument *save.as* which can be set to specify a file name. Setting *save.as=paste("Manufacturing.monitoring.", make.names(date()), sep="")* in the above would make a file name which includes a time stamp. Also, setting the argument *run.again=T* will run the forecast without checking to see if the data has been updated.

The argument *mail.list* allows the output to be mailed to a list of recipients, but it may be more convenient to mail the result to a list server which can be used for distribution purposes. This may be easier to maintain, as the list server list of recipients can be changed at any time (and in automatic mode described next the program does not have to be restarted.)

Step 5 - automatic program to run the monitoring

To run the above and e-mail forecast directly from the Unix command prompt a shell script can be set up as follows:

```
#!/bin/csh
cd /...path to directory...
setenv S_SILENT_STARTUP quiet
Splus <<eofS
r <- simple.monitoring( as above )
manuf.previous.data <- r[[“data”]]
q()
eofS
```

Below it is assumed this is in a file called *manufacturing*. To run this automatically every 20 minutes from 7am to 10am the script

```
#!/bin/csh
```

```
#  the argument should be a script to run
#  between 7am and 10am check every 1200sec = 20 min.
  @ start = 7
  @ stop = 10
  @ f = 1200
lp:
  $1
  set h = `date +%H`
  set m = `date +%M`
  if ($h < $start) then
     @ s = ($start - ( 1 + $h) ) * 3600 + (60 - $m) * 60
  else
     if ($h > ( $stop - 1) ) then
       @ s = $start * 3600 + (23 - $h) * 3600 + (60 - $m) * 60
     else
       @ s = $f
     endif
  endif
  sleep $s
goto lp
```

could be put in a file *monitoring.daemon* and then this can be started at the Unix prompt with the command

unix prompt: *monitoring.daemon manufacturing*

The disadvantage of this approach is that the overhead for starting Splus is fairly heavy and it may be difficult to use your computer for much else from 7am to 10am. (R may be better in this respect.) If you have direct access to the files used for the database then the script could be modified to check time stamps on the files and only run if the file date has changed. If database files are used to store many series, and not all are updated at the same time, then the savings will not be much. At the Bank of Canada another script called *Data.trigger.daemon* can be used to run a Fame procedure to check if the particular series have been updated, and then run *manufacturing* only in that case.

Appendix I: Mini-Reference

Following is a short list of some of the more important functions. The online help contains more complete information on the use of a functions.

OBJECTS

ARMA - define an ARMA *TSmodel*

SS - define a state-space *TSmodel*

TSdata - define a data structure for *TSmodel*s

MODEL INFORMATION

print - display model arrays

summary - summary information about a model

tfplot - plot data or model predictions.

MODEL PROPERTIES

McMillan.degree - calculate the McMillan degree of a model

roots - calculate the roots of a model

stability - check stability of model

MODEL CONVERSION

to.SS - convert to an equivalent state space innovations representation

to.ARMA - convert to an ARMA representation

SIMULATION, ONE-STEP PREDICTIONS & RELATED STATISTICS

simulate - Simulate a model to generate artificial data.

l - evaluate a TSmodel with TSdata and return a TSestModel object

smoother - calculate smoothed state for a state space model.

check.residuals - distribution, autocorrelation and partial autocorrelation of residuals

information.tests - print model selection criteria

MODEL ESTIMATION & REDUCTION

est.VARX.ls - estimate VAR model with exogenous variable using OLS

est.VARX.ar - estimate VAR model with exogenous variable using autocorrelations

est.SS.from.VARX - estimate a VARX model and convert to state space

est.SS.Mittnik - estimate state space model using Mittnik's markov parameter technique

est.max.like - Maximum likelihood estimation of models.

est.black.box - estimate and find the best reduced model

*est.black.box*4 - estimate and find the best reduced model by techniques in Gilbert (1995), also referred to as *bft*

reduction.Mittnik - nested-balanced state space model reduction by svd of Hankel generated from a model

FORECAST AND FORECAST EVALUATION

forecast - generate a forecast from given model and data.

featherForecasts - forecast from specified periods

horizonsForecasts - forecast specified periods ahead

forecastCov - calculate covariance of multi-period ahead forecasts

ESTIMATION EVALUATION

EstEval - evaluate specified estimation techniques using a given true model

out.of.sample.forecastCov.estimatorsWRTdata - evaluate specified estimation techniques using a given data set

Appendix II: TS PADI Data Retrieval

This section describes utilities for retrieving data from an online database. This has been implemented using the TS PADI interface. The examples use series names which are specific to the Bank of Canada.

Building a database plug will typically require some programming effort. This effort can be reduced by using a standardized interface. Code and a description of a prototype of a standard for a Time Series Protocol for Application - Database Interface (TS PADI) is available at *http://www.bank-banque-canada.ca/pgilbert*. The code includes a working S interface to a Fame database. It may also be useful to check with your database software vendor to get an update on the status of commercial support for an interface. PADI also allows direct connection to databases over the Internet, so eventually, when the interface is more widely supported, it may be possible to connect to databases which are not maintained at your site.

Data is retrieved with a description which gives an indication of where the data comes from, which series are model inputs and which are model outputs, any transformations which should be applied to the data, and some padding information indicating whether the series should be padded with *NA*s to the length of the longest available series or truncated to the subset where all data is available for all series. Data is retrieved by using the generic function *freeze()* on the description. When *freeze()* is a applied to an object which is already time series data then the data is simply returned. When applied to a data description object the data is retrieved from the data base. Most of the functions in the DSE library use the function *freeze()* on data, so data descriptions can be used interchangeably with data. For model estimation purposes it is usually desirable to retrieve the data and work with a fixed data set, but once a model is established and is routinely used with newly available data then the data description is more convenient.

The following simple example specifies the series *I37005* from the *ets* server as the single output series, and gives it a more descriptive name. No data transformations are performed.

```
eg2.DSE.data.names <- TSPADIdata( output= “I37005”,
        output.names= “manuf.prod.” , server=“ets”)
```

Setting *output.names* is optional. If they are set then they will be used in many printing and plotting routines. The following line then returns the data.

```
eg2.DSE.data <- freeze(eg2.DSE.data.names)
```

The following example specifies one input and one output series.

```
eg3.DSE.data.names <- TSPADIdata(
   input=”lfsa455”, input.transformations= “percent.change”,
   input.names= “manuf.emp.”,
   output=“i37005”, output.names=“manuf.prod.”,
   output.transformations= “percent.change”,
```

```
    pad.start=F, pad.end =T, server= "ets")
eg3.DSE.data <- freeze(eg3.DSE.data.names)
```

Here is a multivariate example used in Gilbert (1995):

```
 JofF.VAR.data.names <-TSPADIdata(
    input = "B14017", input.transformations= "diff", input.names="R90",
    output = c("P484549", "I37026", "b1627", "b14013",
                    "b4237", "D767608", "b3400", "M.BCPI",
                    "M.JQIND", "M.CUSA0"),
    output.transformations=c("percent.change",
               "percent.change","percent.change",
               "diff", "diff", "percent.change",
               "percent.change", "percent.change",
               "percent.change", "percent.change"),
    output.names=c("CPI", "GDP", "M1", "RL", "TSE300",
               "employment", "PFX", "com. price ind.",
               "US ind. prod.", "US CPI"),
server="ets")
JofF.VAR.data <- freeze(JofF.VAR.data.names)
```

The variables *pad*, *pad.start*, *and pad.end* control what happens at the beginning and end of multivariate data when all series are not available for the same periods. If *pad.start* is *TRUE* then *NAs* are placed at the beginning of series if data is not available, so the multivariate series starts with the first available data. If *pad.start* is *FALSE* then the beginning is truncated so that the first multivariate data point contains values for all variables. Similarly, *pad.end* works with the last periods of the series. *pad* can be used in place of *pad.start* and *pad.end*.

Most estimation routines require a complete data set for all variables (*pad=F*), but for many purposes it is useful to have all the data. The function *trim.na* takes a complete data set and removes padding at both ends. This is a convenient way to remove *NAs* from the beginning and end before estimation. The function *tfwindow* can also be used to truncate series to a desired sample period.

An alternate form for specifying the data names can be given using the function *TSPADIdata2:*

```
 alt.JofF.VAR.data.names <- TSPADIdata2(
    input = list(c("ets", "" , "B14017", "diff", "R90")),
    output = list(
         c("ets", "", "P484549","percent.change", "CPI"),
         c("ets", "", "I37026", "percent.change", "GDP"),
         c("ets", "", "b1627", "percent.change", "M1"),
         c("ets", "", "b14013", "diff", "RL"),
         c("ets", "", "b4237", "diff", "TSE300"),
```

```
c("ets", "", "D767608","percent.change", "employment"),
c("ets", "", "b3400", "percent.change", "PFX"),
c("ets", "", "M.BCPI", "percent.change", "com. price ind."),
c("ets", "", "M.JQIND","percent.change","US ind. prod."),
c("ets", "", "M.CUSA0","percent.change","US CPI")) )
```

The result is the same but this form may be more convenient is some circumstances. For each series the character strings indicate the server, additional server information, the series identifier, any transformation, and finally a series description. The order of these strings is important. The additional server information may be empty, as above, but cannot be omitted. For some servers it may be used to pass information such as a source database. If no data transformation is to be done then the third string should be empty ("").

A smaller example, also used in Gilbert (1995), is given by:

```
eg4.DSE.data.names <-TSPADIdata(
    input = "B14017", input.transformations= "diff", input.names="R90",
    output = c("P484549", "I37026", "D767608", "b3400")
    output.transformations=c("percent.change", "percent.change",
                            "percent.change", "percent.change"),
    output.names=c("CPI", "GDP", "employment", "PFX") ,
    server="ets)
eg4.DSE.data <- freeze(eg4.DSE.data.names)
```

Appendix III: Installation

If you are connected to the Internet and using R then installation can be done using *install.packages(“dse”, “dseplus”)* or *update.packages(“dse”, “dseplus”)*. If you are using R but not connected to the Internet then use the R package installation procedure. (In Unix this is “R INSTALL dse_xxx-x.tar.gz” from the command line or “R INSTALL dse” in the directory above the uncompressed and untarred package, and similarly for dseplus.) If you are using Splus then installation is done with the Unix script called INSTALL. See the Splus installation instructions in the READ.ME file for more details. The latest public version of this software is available at <*http://www.bank-banque-canada.ca/pgilbert*> and should also be on CRAN. If you have not yet installed the software then, before proceeding, please check if a more recent version is available. Also available at the web site are postscript and pdf files of the text Gilbert (1993)

The code should be a complete working system. There are no essential pieces missing, however, there may be references in the documentation (and options in the code) to additional features and functions which are not yet included.

In Splus, the library is attached with *attach()* or *library()*. Users can dynamically load the fortran code with *load.DSE.fortran()*:

library(“DSE”, first=T)
load.DSE.fortran()

In R, the library is attached with

library(“syskern”)
library(“tframe”)
library(“dse1”) #for the base functionality
library(“dse2”) #for functions described later in the guide.

In R the compiled code is automatically loaded.

You should consider putting these lines in your *.First* function, which is automatically executed each time you start. (This is especially advisable in Splus as some of the more advanced functions in this library spawn separate sessions to speed calculations.)

It is necessary for the library to over-ride some functions in some versions of Splus, so it is important that it is near the beginning of the search path.

The DSE library help is integrated into the R help facility. In Splus the help is accessible as HTML documents which can be viewed with any WWW browser. The initial point to load into your browser is the file dsehome.htm.

The core part of this code, discussed in this Guide, has been tested and works well. Errors in the documentation are more likely. Other parts of the code, not discussed in the Guide, may contain more errors. Using equivalent representations there are typically many simple ways to confirm results, and that is strongly advised. All code is provided on an “as is” basis, but please report any errors that you find.

References

Becker, R. A., J. M. Chambers, and A. Wilks. 1988. *The New S Language* Pacific Grove: Wadsworth & Brooks/Cole.

Burns, Patrick. *Spoetry* available at <http://www.seanet.com/~pburns/Spoetry>

Gilbert, P.D. 1993. "State space and ARMA models: An overview of the equivalence." Working Paper 93-4, Bank of Canada.

Gilbert, P.D. 1995 "Combining VAR Estimation and State Space Model Reduction for Simple Good Predictions" *J. of Forecasting: Special Issue on VAR Modelling and Forecasting.* 14:229-250

Gilbert, P.D. 2000 "A note on the computation of time series model roots" *Applied Economics Letters.* 7:423-424

Ihaka, R. and R. Gentleman. 1996, "R: A Language for Data Analysis and Graphics" *Journal of Computational and Graphical Statistics.* 5: 299-314

Krause, A. and M. Olson, *The Basics of S and S-Plus* Springer-Verlag.

Ripley, B.D. 1994. *Introductory Guide to Splus*. Available from statlib by "send SGuide from S"

W.N. Venables, and B. D. Ripley. *Modern Applied Statistics with S-Plus.* Springer-Verlag.