

Modeling and Analysis of Time Series Data

Chapter 16: A case study of financial volatility and a POMP model with observations driving latent dynamics

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Outline

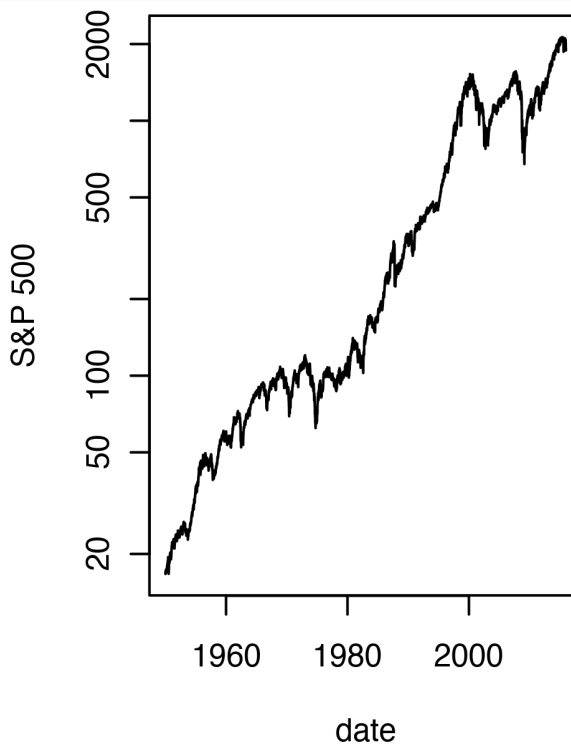
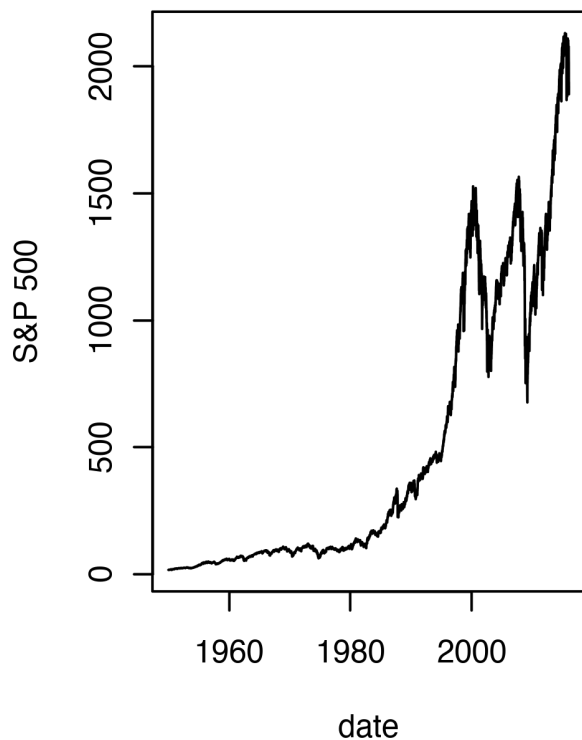
- 1 Time series models for financial volatility
 - The ARCH and GARCH models
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Introduction

- Returns on investments in stock market indices or large companies are often found to be approximately uncorrelated.
- If investment returns are substantially correlated, investors can study their time series behavior and make money.
- If the investment is non-liquid (i.e., not reliably tradeable), or expensive to trade, then it might be hard to make money even if you can statistically predict a positive expected return.
- Otherwise, the market may notice a favorable investment opportunity. More buyers will lead to higher prices, and the opportunity will disappear.
- Consequently, most readily traded investments (e.g., stock market indices, or stock of large companies) have close to uncorrelated returns. 回报率几乎都不相关
- The variability of the returns (called the volatility) can fluctuate considerably. Understanding this volatility is important for quantifying and managing the risk of investments.

- Recall the daily S&P 500 data that we saw earlier, in Chapter 3.

```
dat <- read.table("sp500.csv", sep=",", header=TRUE)
plot(as.Date(dat$Date), dat$Close,
     xlab="date", ylab="S&P 500", type="l")
plot(as.Date(dat$Date), dat$Close, log="y",
     xlab="date", ylab="S&P 500", type="l")
```



Returns, absolute returns, and autocorrelation

- We write $\{z_n, n = 1, \dots, N\}$ for the S&P 500 index value.
- We write the return, i.e., the difference of the log of the index, as

$$y_n^* = \log(z_n) - \log(z_{n-1}).$$

* We saw in Chapter 3 that $y_{2:N}^*$ has negligible sample autocorrelation.

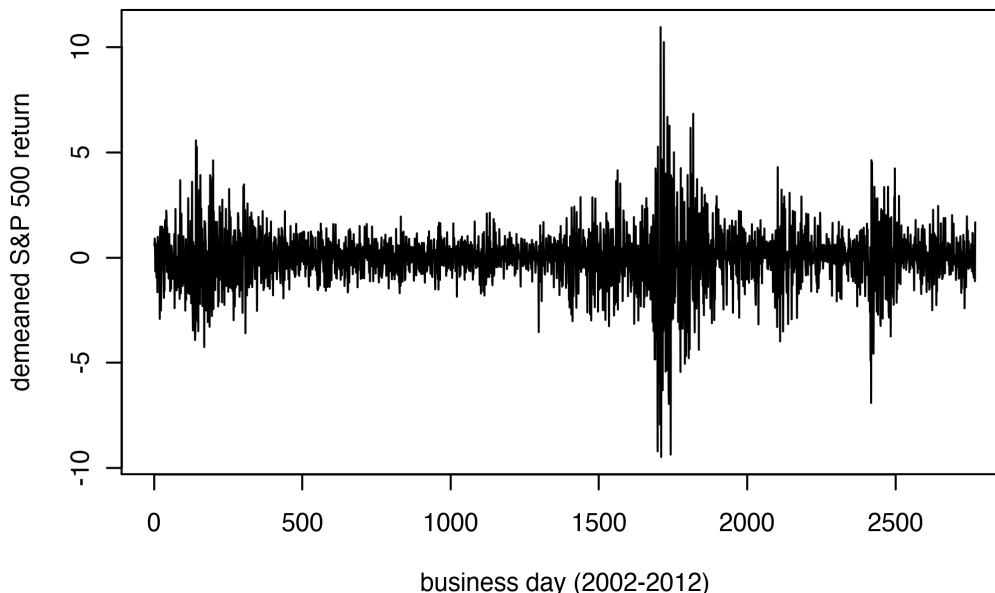
- However, the absolute deviations from average,

$$a_n^* = \left| y_n^* - \frac{1}{N-1} \sum_{k=2}^N y_k^* \right|$$

have considerable sample autocorrelation.

绝对值误差有很强的自相关性

- We fit models to the demeaned daily returns for the S&P 500 index for 2002-2012, to compare with Bretó (2014).



Question 16.1. Is it appropriate to fit a stationary model to this series, or do we have evidence for violation of stationarity? Explain.

The ARCH model

- ARCH and GARCH models are widely used for financial time series modeling. We follow Cowpertwait and Metcalfe (2009) to introduce these models; see also Section 5.4 of (Shumway and Stoffer, 2017).
- An order p **autoregressive conditional heteroskedasticity** model, known as ARCH(p), has the form

$$Y_n = \epsilon_n \sqrt{V_n},$$

where $\epsilon_{1:N}$ is white noise and

隐状态和上一个时点的观测值有关

$$V_n = \alpha_0 + \sum_{j=1}^p \alpha_j Y_{n-j}^2.$$

- If $\epsilon_{1:N}$ is Gaussian, then $Y_{1:N}$ is called a Gaussian ARCH(p). Note, however, that a Gaussian ARCH model is not a Gaussian process, just a process driven by Gaussian noise.
- If $Y_{1:N}$ is a Gaussian ARCH(p), then $Y_{1:N}^2$ is AR(p), but not Gaussian AR(p).

The GARCH model

- The **generalized ARCH** model, known as GARCH(p,q), has the form

$$Y_n = \epsilon_n \sqrt{V_n},$$

where

$$V_n = \alpha_0 + \sum_{j=1}^p \alpha_j Y_{n-j}^2 + \sum_{k=1}^q \beta_k V_{n-k}$$

and $\epsilon_{1:N}$ is white noise. 隐状态和上一个时点的观测值和隐状态都有关

- The GARCH(1.1) model is a popular choice (Cowpertwait and Metcalfe, 2009) which can be fitted using `garch()` in the `tseries` R package.

Fitting a GARCH model

```
require(tseries)
fit.garch <- garch(sp500.ret.demeaned, grad = "numerical",
  trace = FALSE)
L.garch <- tseries::logLik.garch(fit.garch)
```

- This 3-parameter model has a maximized log likelihood of -4019.7 .
- It appears that a bug in this version of `tseries` means that simply `logLik(fit.garch)` does not work.
- From `?garch` we learn this is actually a conditional log likelihood given the first $\max(p, q)$ values. 设定p和q之后的似然函数

Question 16.2. It is usually inappropriate to present numerical results to five significant figures. Does that apply to the log likelihood reported here? Why?

- We are now in a position to employ the framework of likelihood-based inference for GARCH models. In particular, profile likelihood, likelihood ratio tests, and AIC are available.
- We can readily simulate from a fitted GARCH model, if we want to investigate properties of a fitted model that we don't know how to compute analytically.
- However, GARCH is a black-box model, in the sense that the parameters don't have clear interpretation. We can develop an appropriate GARCH(p,q) model, and that may be useful for forecasting, but it won't help us understand more about how financial markets work.
- We seek models that let us entertain different hypotheses about how volatility behaves.

Garch模型的可解释性差,只有应用价值,却不能帮助我们加深理解

Stochastic volatility models

- Volatility can be modeled as a latent stochastic process, partially observed via the returns. 通过收益率驱动来模拟波动率的变化
- A Markovian assumption for volatility leads to a POMP model.
- As usual for POMP modeling, additional dependence (on previous lags or other variables) can be included.
- These are called **stochastic volatility models**.
- The basic stochastic volatility model (Kastner, 2016) is

Y是观测值

X时依赖于时间序列数据和
随机误差生成的对数波动率

sigma是参数

$$Y_n = \epsilon_n \exp\{X_n/2\} \quad (1)$$

$$X_n = \mu + \phi(X_{n-1} - \mu) + \sigma\eta_n \quad (2)$$

$$X_0 = \mu + \frac{\sigma}{\sqrt{1 - \phi^2}}\eta_0 \quad (3)$$

where ϵ_n and η_n are iid normal[0, 1]. Here, X_n is the log volatility.

- We can use the flexibility of the POMP framework to see if we can do better.

Volatility leverage

- It is a fairly well established empirical observation that negative shocks to a stockmarket index are associated with a subsequent increase in volatility.
- This phenomenon is called **leverage**. 标的价格大幅下跌后,会大幅增加波动率
- Here, we formally define leverage, R_n on day n as the correlation between index return on day $n - 1$ and the increase in the log volatility from day $n - 1$ to day n . R_n 是收益率和波动率变化的相关系数
- Models have been proposed which incorporate leverage into the dynamics (Bretó, 2014).
- We present a pomp implementation of Bretó (2014), which models R_n as a random walk on a transformed scale,

$$R_n = \frac{\exp\{2G_n\} - 1}{\exp\{2G_n\} + 1},$$

where $\{G_n\}$ is the usual, Gaussian random walk.

Time-varying parameters

- A special case of this model, with the Gaussian random walk having standard deviation zero, is a fixed leverage model.
- The POMP framework provides a general approach to time-varying parameters. Considering a parameter as a latent, unobserved random process that can progressively change its value over time (following a random walk, or some other stochastic process) leads to a POMP model. 模型参数全部作为隐变量处理
- The resulting POMP model is usually non-Gaussian, even when the original model is Gaussian and the perturbations are Gaussian, unless the time-varying parameter enters the model additively.
- Many real-world systems are non-stationary and could be investigated using models with time-varying parameters.

- Following the notation and model representation in equation (4) of Bretó (2014), we propose a model,

$$Y_n = \exp\{H_n/2\} \epsilon_n, \quad \text{这里引入了}\epsilon_n \quad (4)$$

$$H_n = \mu_h(1 - \phi) + \phi H_{n-1} + \beta_{n-1} R_n \exp\{-H_{n-1}/2\} + \omega_n, \quad (5)$$

$$G_n = G_{n-1} + \nu_n, \quad (6)$$

where $\beta_n = Y_n \sigma_\eta \sqrt{1 - \phi^2}$, $\{\epsilon_n\}$ is an iid $N(0, 1)$ sequence, $\{\nu_n\}$ is an iid $N(0, \sigma_\nu^2)$ sequence, and ω_n is $N(0, \sigma_{\omega,n}^2)$ with

$$\sigma_{\omega,n}^2 = \sigma_\eta^2(1 - \phi^2)(1 - R_n^2).$$

- Here, H_n is the log volatility. The latent state is $X_n = (G_n, H_n)$, noting that R_n is a function of G_n .

- Y_n 是观测值, H_n 是对数波动率, 但因为epsilon的存在无法全部观测
- R_n 是收益率和波动率的相关性, 由G驱动
- epsilon, sigma, nu, omega都是i.i.d的随机成分

Building a POMP model

- A complication is that transition of the latent variables from (G_n, H_n) to (G_{n+1}, H_{n+1}) depends on the observable variable Y_n .
- This situation appears to be a violation of the POMP model structure.
- It is not so uncommon. For example, the same thing happens in a dynamic system subject to a control measure which is a function of the observed data.
- We can write out an extended model to fit this situation into the POMP structure, to provide access to methodology for POMP models.

隐状态的生成会和观测值有关,看起来好像和POMP的定义不符合,但相似的场景也出现在控制系统中

- Formally, a POMP representation has state variable $X_n = (G_n, H_n, Y_n)$ and measurement variable Y_n being perfect observation of this component of X_n . 用X矩阵来表示所有隐状态
- When the latent state is **continuous** and there is no measurement error, the basic particle filter fails since all prediction particles are inconsistent with the data. We need a modification of sequential Monte Carlo (SMC).
- We write the filtered particle j at time $n - 1$ as

$$X_{n-1,j}^F = (G_{n-1,j}^F, H_{n-1,j}^F, y_{n-1}^*).$$

- Now we can construct prediction particles at time n ,

$$(G_{n,j}^P, H_{n,j}^P) \sim f_{G_n, H_n | G_{n-1}, H_{n-1}, Y_{n-1}}(g_n | G_{n-1,j}^F, H_{n-1,j}^F, y_{n-1}^*)$$

with corresponding weight

$$w_{n,j} = f_{Y_n | G_n, H_n}(y_n^* | G_{n,j}^P, H_{n,j}^P).$$

- Resampling with probability proportional to these weights gives an SMC representation of the filtering distribution at time n .
- A derivation of this is given as an Appendix.

- We can coerce the basic sequential Monte Carlo algorithm, implemented as `pfilter` in **pomp**, into carrying out this calculation by building two different `pomp` objects, one to do filtering and another to do simulation.
- For the implementation in **pomp**, we proceed to write Csnippet code for the two versions of `rprocess`.

```
sp500_statenames <- c("H", "G", "Y_state")
sp500_rp_names <- c("sigma_nu", "mu_h", "phi", "sigma_eta")
sp500_ivp_names <- c("G_0", "H_0")
sp500_paramnames <- c(sp500_rp_names, sp500_ivp_names)
```

```

rproc1 <- "
  double beta,omega,nu;
  omega = rnorm(0,sigma_eta * sqrt( 1- phi*phi ) *
    sqrt(1-tanh(G)*tanh(G)));
  nu = rnorm(0, sigma_nu);
  G += nu;
  beta = Y_state * sigma_eta * sqrt( 1- phi*phi );
  H = mu_h*(1 - phi) + phi*H + beta * tanh( G )
    * exp(-H/2) + omega;
"

rproc2.sim <- "
  Y_state = rnorm( 0,exp(H/2) );
"

rproc2.filt <- "
  Y_state = covaryt;
"

sp500_rproc.sim <- paste(rproc1,rproc2.sim)
sp500_rproc.filt <- paste(rproc1,rproc2.filt)

```

```
sp500_rinit <- "  
  G = G_0;  
  H = H_0;  
  Y_state = rnorm( 0,exp(H/2) );  
"
```

```
sp500_rmeasure <- "  
  y=Y_state;  
"
```

```
sp500_dmeasure <- "  
  lik=dnorm(y,0,exp(H/2),give_log);  
"
```

Parameter transformations

- For optimization procedures such as iterated filtering, it is convenient to transform parameters to be defined on the whole real line.
- We therefore write transformation functions for σ_η , σ_ν and ϕ ,

```
library(pomp)
sp500_partrans <- parameter_trans(
  log=c("sigma_eta", "sigma_nu"),
  logit="phi"
)
```

- We can now build a pomp object suitable for filtering, and parameter estimation by iterated filtering or particle MCMC.
- Note that the data are also placed in a covariate slot.
- This is a device to allow the state process evolution to depend on the data. In a POMP model, the latent process evolution depends only on the current latent state. In **pomp**, the consequence of this structure is that `rprocess` doesn't have access to the observation process.
- However, a POMP model does allow for the possibility for the basic elements to depend on arbitrary covariates. In **pomp**, this means `rprocess` has access to a covariate slot.
- The code below gives an example of how to fill the covariate slot and how to use it in `rprocess`.

本来pomp模型的定义是无法使用观测值来推动状态转换的,因此我们先把观测值保存在另一个时序数据中,作为covariate来推动状态转换

```

sp500.filt <- pomp(data=data.frame(
  y=sp500.ret.demeaned,time=1:length(sp500.ret.demeaned)),
  statenames=sp500_statenames,
  paramnames=sp500_paramnames,
  times="time",
  t0=0,
  covar=covariate_table(
    time=0:length(sp500.ret.demeaned),
    covaryt=c(0,sp500.ret.demeaned),
    times="time"),
  rmeasure=Csnippet(sp500_rmeasure),
  dmeasure=Csnippet(sp500_dmeasure),
  rprocess=discrete_time(step.fun=Csnippet(sp500_rproc.filt),
    delta.t=1),
  rinit=Csnippet(sp500_rinit),
  partrans=sp500_partrans
)

```

- Simulating from the model is convenient for developing and testing the code, as well as to investigate a fitted model:

```
params_test <- c(  
  sigma_nu = exp(-4.5),  
  mu_h = -0.25,  
  phi = expit(4),  
  sigma_eta = exp(-0.07),  
  G_0 = 0,  
  H_0=0  
)  
  
sim1.sim <- pomp(sp500.filt,  
  statenames=sp500_statenames,  
  paramnames=sp500_paramnames,  
  rprocess=discrete_time(  
    step.fun=Csnippet(sp500_rproc.sim),delta.t=1)  
)  
  
sim1.sim <- simulate(sim1.sim,seed=1,params=params_test)
```

- Now. to build the filtering object from `sim1.sim`, we need to copy the new simulated data into the covariate slot, and put back the appropriate version of `rprocess`.

```
sim1.filt <- pomp(sim1.sim,
  covar=covariate_table(
    time=c(timezero(sim1.sim),time(sim1.sim)),
    covaryt=c(obs(sim1.sim),NA),
    times="time"),
  statenames=sp500_statenames,
  paramnames=sp500_paramnames,
  rprocess=discrete_time(
    step.fun=Csnippet(sp500_rproc.filt),delta.t=1)
)
```


Filtering on simulated data

- We check that we can indeed filter and re-estimate parameters successfully for this simulated data.
- As previously discussed, we set up code to switch between different levels of computational intensity:

```
run_level <- 3
sp500_Np <-      switch(run_level, 100, 1e3, 2e3)
sp500_Nmif <-    switch(run_level, 10, 100, 200)
sp500_Nreps_eval <- switch(run_level, 4, 10, 20)
sp500_Nreps_local <- switch(run_level, 10, 20, 20)
sp500_Nreps_global <- switch(run_level, 10, 20, 100)
```

- We carry out replications in parallel, using all available cores on either a laptop or a single node of a SLURM cluster.

```
library(doParallel)
cores <- as.numeric(Sys.getenv('SLURM_NTASKS_PER_NODE', unset=NA))
if(is.na(cores)) cores <- detectCores()
registerDoParallel(cores)
library(doRNG)
registerDoRNG(34118892)
```

```
stew(file=sprintf("pf1-%d.rda",run_level),{
  t.pf1 <- system.time(
    pf1 <- foreach(i=1:sp500_Nreps_eval,
      .packages='pomp') %dopar% pfilter(sim1.filt,Np=sp500_Np))
  })
(L.pf1 <- logmeanexp(sapply(pf1,logLik),se=TRUE))

                                se
-3658.7879118      0.1459427
```

- In 4.3 seconds, we obtain a log likelihood estimate of -3658.79 with a Monte Carlo standard error of 0.15. 使用logmeanexp消除误差可以获得无偏结果
- Notice that the replications are averaged using the logmeanexp function, since the likelihood estimate is unbiased on the natural scale but not the log scale.
- We could test the numerical performance of an iterated filtering likelihood maximization algorithm on simulated data.
- We could also study the statistical performance of maximum likelihood estimators and profile likelihood confidence intervals on simulated data.
- However, here we are going to cut to the chase and start fitting models to data.

Fitting the stochastic leverage model to S&P500 data

- We are now ready to try out iterated filtering on the S&P500 data. We will use the IF2 algorithm of Ionides *et al.* (2015), implemented by `mif2`.

```
sp500_rw.sd_rp <- 0.02
sp500_rw.sd_ivp <- 0.1
sp500_cooling.fraction.50 <- 0.5
sp500_rw.sd <- rw.sd(
  sigma_nu = sp500_rw.sd_rp,
  mu_h     = sp500_rw.sd_rp,
  phi      = sp500_rw.sd_rp,
  sigma_eta = sp500_rw.sd_rp,
  G_0      = ivp(sp500_rw.sd_ivp),
  H_0      = ivp(sp500_rw.sd_ivp)
)
```

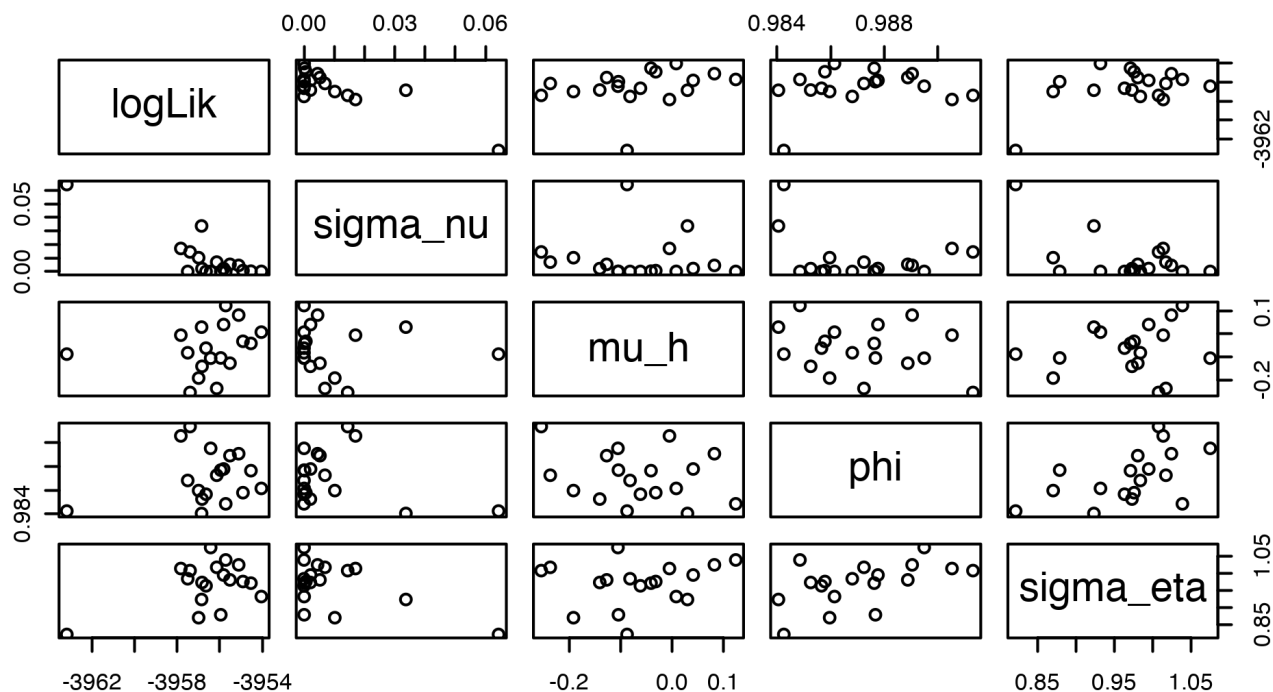
```

stew(file=sprintf("mif1-%d.rda",run_level),{
  t.if1 <- system.time({
    if1 <- foreach(i=1:sp500_Nreps_local,
      .packages='pomp', .combine=c) %dopar% mif2(sp500.filt,
        params=params_test,
        Np=sp500_Np,
        Nmif=sp500_Nmif,
        cooling.fraction.50=sp500_cooling.fraction.50,
        rw.sd = sp500_rw.sd)
    L.if1 <- foreach(i=1:sp500_Nreps_local,
      .packages='pomp', .combine=rbind) %dopar% logmeanexp(
        replicate(sp500_Nreps_eval, logLik(pfilter(sp500.filt,
          params=coef(if1[[i]]),Np=sp500_Np))), se=TRUE)
  })
})
r.if1 <- data.frame(logLik=L.if1[,1],logLik_se=L.if1[,2],
  t(sapply(if1,coef)))
if (run_level>1) write.table(r.if1,file="sp500_params.csv",
  append=TRUE,col.names=FALSE,row.names=FALSE)

```

- This investigation took 20 minutes.
- The repeated stochastic maximizations can also show us the geometry of the likelihood surface in a neighborhood of this point estimate:

```
pairs(~logLik+sigma_nu+mu_h+phi+sigma_eta,  
data=subset(r.if1,logLik>max(logLik)-20))
```



Likelihood maximization using randomized starting values

- As for our other case studies, carrying out searches starting randomly throughout a large box can lead to reasonable evidence for successful global maximization.
- For our volatility model, a box containing plausible parameter values might be

```
sp500_box <- rbind(  
  sigma_nu=c(0.005,0.05),  
  mu_h      =c(-1,0),  
  phi = c(0.95,0.99),  
  sigma_eta = c(0.5,1),  
  G_0 = c(-2,2),  
  H_0 = c(-1,1)  
)
```

进行全局搜索

```

stew(file=sprintf("box_eval-%d.rda",run_level),{
  t.box <- system.time({
    if.box <- foreach(i=1:sp500_Nreps_global,
      .packages='pomp',.combine=c) %dopar% mif2(if1[[1]],
        params=apply(sp500_box,1,function(x)runif(1,x)))
    L.box <- foreach(i=1:sp500_Nreps_global,
      .packages='pomp',.combine=rbind) %dopar% {
      logmeanexp(replicate(sp500_Nreps_eval, logLik(pfilter(
        sp500.filt,params=coef(if.box[[i]]),Np=sp500_Np))),
        se=TRUE)}
  })
})
r.box <- data.frame(logLik=L.box[,1],logLik_se=L.box[,2],
  t(sapply(if.box,coef)))
if(run_level>1) write.table(r.box,file="sp500_params.csv",
  append=TRUE,col.names=FALSE,row.names=FALSE)
summary(r.box$logLik,digits=5)

```

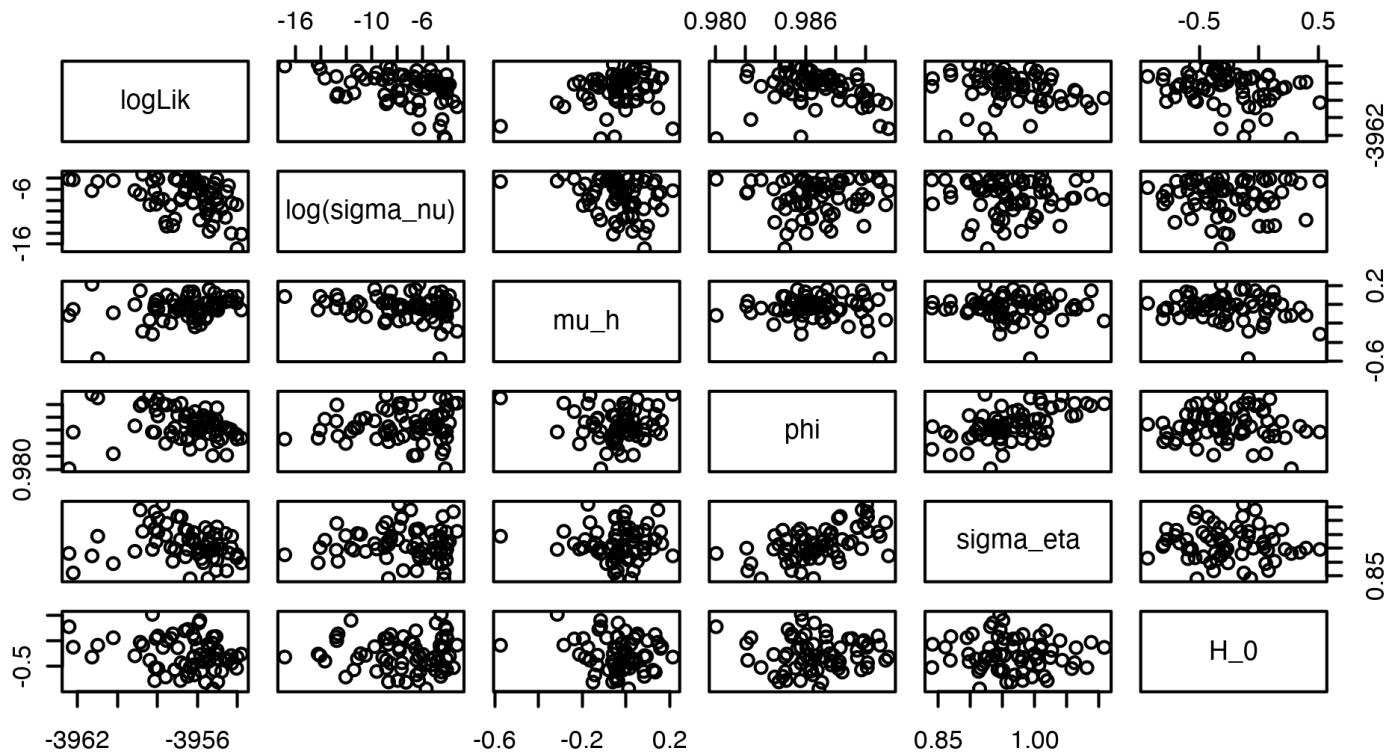
| Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|-------|---------|--------|-------|---------|-------|
| -3996 | -3986 | -3957 | -3966 | -3956 | -3954 |

- This search took 64.1 minutes.
- The best likelihood found was -3953.8 with a standard error of 0.2.
- We see that optimization attempts from diverse remote starting points can approach our MLE, but do not exceed it. This gives us some reasonable confidence in our MLE.
- Plotting these diverse parameter estimates can help to give a feel for the global geometry of the likelihood surface

```

pairs(~logLik+log(sigma_nu)+mu_h+phi+sigma_eta+H_0,
      data=subset(r.box,logLik>max(logLik)-10))

```



- This preliminary analysis does not show clear evidence for the hypothesis that $\sigma_\nu > 0$.
- That is likely because we are studying only a subset of the 1988 to 2012 dataset analyzed by Bretó (2014).
- Also, it might help to refine our inference by computing a likelihood profile over σ_ν .

Benchmark likelihoods for alternative models

使用传统的GARCH模型来作为benchmark和pomp模型来对比

- To assess the overall success of the model, it is helpful to put the log likelihoods in the context of simpler models, called **benchmarks**.
- Benchmarks provide a complementary approach to residual analysis and the investigation of simulations from the fitted model.
- The GARCH(1,1) model for this dataset has a maximized likelihood of -4019.7 with 3 fitted parameters.
- Our stochastic volatility model, with time-varying leverage, model has a maximized log likelihood of -3953.8 with 6 fitted parameters. AIC favors the stochastic volatility model.
- A model which both fits better and has meaningful interpretation has clear advantages over a simple statistical model.
- The disadvantage of the sophisticated modeling and inference is the extra effort required.

Can a mechanistic model be helpful if it loses to a non-mechanistic alternative?

- Sometimes, the mechanistic model does not beat simple benchmark models. That does not necessarily mean the mechanistic model is entirely useless. 似然函数表现好的模型不一定最合适,因为还要分析可解释性
- We may be able to learn about the system under investigation from what a scientifically interpretable model fails to explain.
- We may be able to use preliminary results to improve the model, and subsequently beat the benchmarks.
- If the mechanistic model fits disastrously compared to the benchmark, our model is probably missing something important. We must reconsider the model, based on clues we might obtain by carrying out residual analysis and looking at simulations from the fitted model.

Appendix: Proper weighting for a partially plug-and-play algorithm with a perfectly observed state space component

- Suppose a POMP model with $X_n = (U_n, V_n)$ and measurement model $f_{Y_n|X_n}(y_n | u_n, v_n) = f_{Y_n|V_n}(y_n | v_n)$, depending only on v_n .
- The proper weight for an SMC proposal density $q_n(x_n | x_{n-1})$ is

$$w_n(x_n | x_{n-1}) = \frac{f_{Y_n|X_n}(y_n^* | x_n) f_{X_n|X_{n-1}}(x_n | x_{n-1})}{q_n(x_n | x_{n-1})}.$$

- Consider the proposal $q_n(u_n, v_n | x_{n-1}) = f_{U_n|X_{n-1}}(u_n | x_{n-1}) g_n(v_n)$. This is partially plug-and-play, in the sense that the U_n part of the proposal is drawn from a simulator of the dynamic system.
- Computing the weights, we see that the transition density for the U_n component cancels out and does not have to be computed, i.e.,

$$\begin{aligned} w_n(x_n | x_{n-1}) &= \frac{f_{Y_n|V_n}(y_n^* | v_n) f_{U_n|X_{n-1}}(u_n | x_{n-1}) f_{V_n|U_n, X_{n-1}}(v_n | u_n, x_{n-1})}{f_{U_n|X_{n-1}}(u_n | x_{n-1}) g_n(v_n)} \\ &= \frac{f_{Y_n|V_n}(y_n^* | v_n) f_{V_n|U_n, X_{n-1}}(v_n | u_n, x_{n-1})}{g_n(v_n)}. \end{aligned}$$

- Now consider the case where the V_n component of the state space is perfectly observed, i.e., $Y_n = V_n$. In this case,

$$f_{Y_n|V_n}(y_n|v_n) = \delta(y_n - v_n),$$

interpreted as a point mass at v_n in the discrete case and a singular density at v_n in the continuous case.

- We can choose $g_n(v_n)$ to depend on the data, and a natural choice is

$$g_n(v_n) = \delta(y_n^* - v_n),$$

for which the proper weight is

$$w_n(x_n|x_{n-1}) = f_{Y_n|U_n, X_{n-1}}(y_n^*|u_n, x_{n-1}).$$

- This is the situation in the context of our case study, with $U_n = (G_n, H_n)$ and $V_n = Y_n$.

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