Title

code - courseName

Christian Oppegård Moen

dd-mm-yyyy

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library(viridis)	

GARCH(p,q)

Definitions for notational purposes:

- $\mathcal{R}_1 = (r_1, ..., r_{max(p,q)})$
- $\mathcal{R}_2 = (r_t, ..., r_{t+max(p,q)})$
- $\alpha = (\alpha_0, ..., \alpha_n)$
- $\beta = (\beta_1, ..., \beta_q)$
- $\mathbf{r}_{tp} = (1, r_{t-1}, ..., r_{t-p})^{\top}$
- $\sigma_{tq}^2 = (\sigma_{t-1}^2, ..., \sigma_{t-q}^p)^\top$

GARCH(p, q) is given by

$$r_t = \sigma_t \epsilon_t, \tag{1}$$

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^p \alpha_j r_{t-j}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2.$$
 (2)

$$\sigma_t^2 = \alpha r_{tp}^2 + \beta \sigma_{tq}^2. \tag{3}$$

We know that $r_t | \mathcal{R}_2 \sim \mathcal{N}(0, \sigma_t^2)$

The log likelihood $l(\alpha, \beta | \mathcal{R}_1) \propto -\ln L(\alpha, \beta | \mathcal{R}_1)$ is given by

$$l(\boldsymbol{\alpha}, \boldsymbol{\beta}|\mathcal{R}_1) = \sum_{t=m+1}^n \ln(\sigma_t^2) + \frac{r_t^2}{\sigma_t^2}$$
(4)

In the following chunk we implement the so called critical function.

```
garchLL = function(params, r, p = 1, q = 0) {
                   n = length(r)
                   m = max(p, q)
                   alpha = exp(params[1:(p + 1)])
                   if (q == 0) {
                                      beta = 0
                   } else {
                                       beta = exp(params[-(1:(p + 1))])
                   }
                   # initialize variance and set first m values
                   sigma_sq = numeric(n)
                   sigma_sq[1:m] = t(alpha) %*% c(1, r[p:1]^2) # should they be zero?
                    \# sigma_sq[1:m] = 0 \# says so above eq. (5.52)
                   # Iteratively compute each variance
                   for (t in (m + 1):n) {
                                       sigma_sq[t] = sum(alpha * c(1, r[(t - 1):(t - p)]^2)) + sum(beta * sigma_sq[(t - p)]
                                                           1):(t - q)])
```

```
}
ll = sum(log(sigma_sq) + r^2/sigma_sq)
return(ll)
}
```

The variance σ_t^2 can be estimated by one-step-ahead forecasting given by

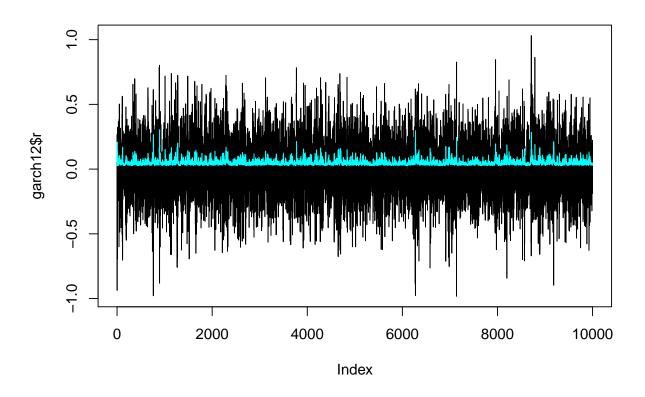
$$\hat{\sigma}_t^2 = \hat{\alpha} r_{tp}^2 + \hat{\beta} \hat{\sigma}_{tq}^2 \tag{5}$$

```
sigmaForecast = function(mod) {
    n = mod n
    m = mod\$m
    p = mod p
    r = mod r
    alpha = mod\$estim[1:(p + 1)]
    if (mod\$q == 0)
        {
            beta = 0
            q = 1
        } # If ARCH(p) model
 else {
        beta = mod\$estim[-(1:(p + 1))]
        q = mod q
    }
    sf = numeric(n) # sigma squared forecasts
    \# sf[1:p] = sum(alpha*c(1,r[p:1]^2)) sf[1:q] = 0 sf[1:m] =
    \# alpha[1]/(1-sum(c(alpha, beta))) \# GPT
    sf[1:m] = sum(alpha * c(1, r[1:p]^2)) # used in sim test
    for (t in (m + 1):n) {
        sf[t] = sum(alpha * c(1, r[(t - 1):(t - p)]^2)) + sum(beta * sf[(t - 1):(t - p)]^2))
            q)])
    }
    return(sf)
}
# TODO: make garch function
Garch = function(r, p = 1, q = 0, init = c(0.1, 0.1)) {
    n = length(r)
    alpha = init[1:(p + 1)]
    if (q == 0)
            beta = 0
            q = 1
        } # If ARCH(p) model
 else {
        beta = init[-(1:(p + 1))]
        q = q
    }
```

Tests

```
testModel = function(mod) {
              n = mod n
              m = mod\$m
              p = mod p
              alpha = mod$paramSim[1:(p + 1)]
              if (mod\$q == 0) {
                            beta = 0
                            q = 1
              } else {
                            beta = mod paramSim[-(1:(p + 1))]
                            q = mod q
              }
              r = numeric(n)
              r[1:m] = rnorm(m)
              sigma_sq = numeric(n)
              sigma_sq[1:m] = sum(alpha * c(1, r[1:p]^2))
              \# sigma_sq[1:m] = alpha[1]/(1-sum(c(alpha, beta))) \# GPT
               # browser()
              for (t in (m + 1):n) {
                             sigma_sq[t] = sum(alpha * c(1, r[(t - 1):(t - p)]^2)) + sum(beta * sigma_sq[(t - p)]^2)) + sigma_sq[(t - p)]^2)) + sigma_sq[(t - p)]^2) + 
                                           1):(t - q)])
                            r[t] = rnorm(1, sd = sqrt(sigma_sq[t]))
              }
               # browser() estimation
              estim = exp(optim(par = log(mod$init), fn = garchLL, r = r, p = p, q = q, method = "BFGS")$par)
              comparison = (rbind(real = mod$paramSim, estim = estim, init = mod$init))
              return(list(r = r, estim = estim, comparison = comparison))
}
```

```
set.seed(420)
arch1 = list(p = 1, q = 0, m = 1, n = 10000, init = rep(0.1, 2), paramSim = c(0.01, arch1 = 1)
    0.2))
testResult = testModel(arch1)
testResult$comparison
##
                [,1]
                          [,2]
## real 0.010000000 0.2000000
## estim 0.009775681 0.1997736
## init 0.10000000 0.1000000
# qqnorm(testResult$r) plot(testResult$r)
set.seed(420)
garch12 = list(p = 1, q = 2, m = 2, n = 10000, init = rep(0.1, 4), paramSim = c(0.01, 4)
    0.2, 0.1, 0.5))
testResult = testModel(garch12)
garch12$estim = testResult$estim
round(testResult$comparison, 3)
         [,1] [,2] [,3] [,4]
## real 0.01 0.20 0.100 0.500
## estim 0.01 0.21 0.112 0.464
## init 0.10 0.10 0.100 0.100
garch12$r = testResult$r
garch12$sigmaForecast = sigmaForecast(garch12)
plot(garch12$r, type = "1")
lines(garch12$sigmaForecast, col = "cyan")
```



Real data (HOW YOU FIT IT AND VIEW IT)

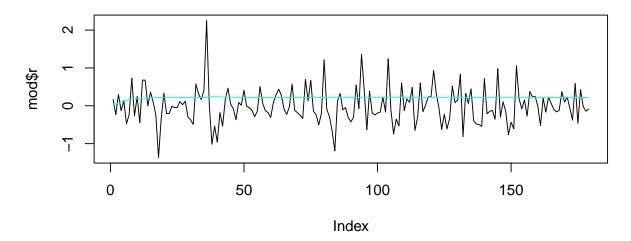
```
df <- read.csv("projectdata.csv", header = T, sep = ";", dec = ",", stringsAsFactors = FALSE)

# qqnorm(r) plot(r, type = 'l')

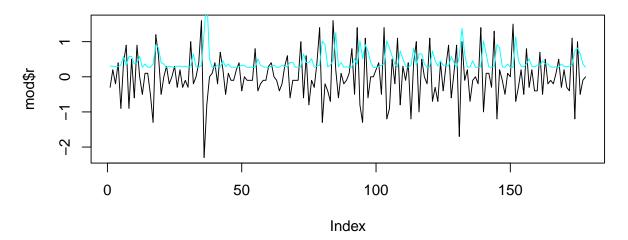
# make data to fit
fit = lm(Inflation ~ Unemployed + Consumption + InterestRate, data = df)
r = df$Inflation - fit$fitted.values
d = diff(df$Inflation)
par(mfrow = c(2, 1))
# inflation - regression
garch12regr = Garch(r, p = 1, q = 2, init = rep(0.1, 1 + 2 + 1))
modResults(garch12regr, main = "garch(1,2) on regression")

# diff inflation
garch12 = Garch(d, p = 1, q = 2, init = rep(0.1, 1 + 2 + 1))
modResults(garch12, "garch(1,2) on diff")</pre>
```

garch(1,2) on regression



garch(1,2) on diff



```
par(mfrow = c(1, 1))

par(mfrow = c(3, 2))
```

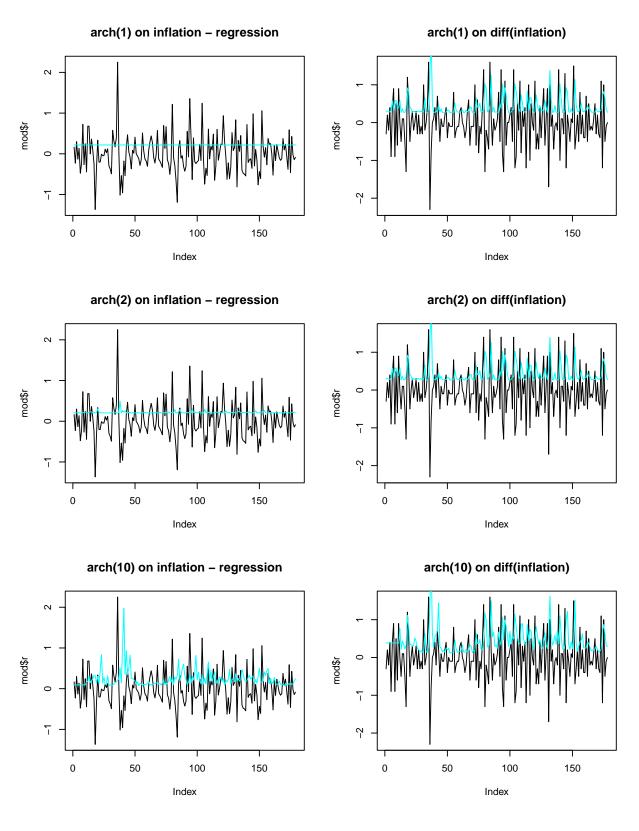
```
arch1regr = Garch(r, p = 1, q = 0, init = rep(0.1, 2))
modResults(arch1regr, main = "arch(1) on inflation - regression")

arch1d = Garch(d, p = 1, q = 0, init = rep(0.1, 2))
modResults(arch1d, main = "arch(1) on diff(inflation)")

arch2regr = Garch(r, p = 2, q = 0, init = rep(0.1, 3))
modResults(arch2regr, main = "arch(2) on inflation - regression")

arch2d = Garch(d, p = 2, q = 0, init = rep(0.1, 3))
```

```
modResults(arch2d, "arch(2) on diff(inflation)")
arch10regr = Garch(r, p = 10, q = 0, init = rep(0.1, 11))
modResults(arch10regr, main = "arch(10) on inflation - regression")
arch10d = Garch(d, p = 10, q = 0, init = rep(0.1, 11))
modResults(arch10d, "arch(10) on diff(inflation)")
```



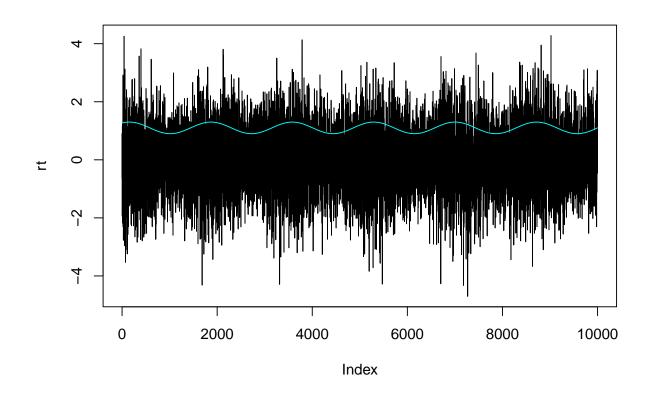
par(mfrow = c(1, 1))

```
list(arch1regr = arch1regr$estim, arch1d = arch1d$estim, arch2regr = arch2regr$estim,
   arch2d = arch2d$estim, arch10regr = arch10regr$estim, arch10d = arch10d$estim)
## $arch1regr
## [1] 2.172051e-01 2.631814e-05
##
## $arch1d
## [1] 0.2681048 0.3845943
## $arch2regr
## [1] 2.040528e-01 2.842043e-05 5.669071e-02
##
## $arch2d
## [1] 2.673872e-01 3.877460e-01 9.556793e-05
##
## $arch10regr
## [1] 6.607910e-02 1.507028e-06 7.553767e-02 4.280618e-05 1.562249e-01
## [6] 3.652726e-01 2.839493e-07 8.483807e-02 2.002727e-06 6.598773e-07
## [11] 1.301979e-01
##
## $arch10d
## [1] 1.143832e-01 4.845580e-01 5.315562e-08 2.358752e-08 5.056129e-02
## [6] 6.419528e-02 5.766002e-08 2.064997e-01 3.922694e-09 4.332273e-13
## [11] 4.898945e-08
models = list(arch1regr = arch1regr, arch1d = arch1d, arch2regr = arch2regr, arch2d = arch2d,
    arch10regr = arch10regr, arch10d = arch10d, garch12regr = garch12regr, garch12 = garch12)
```

Make more models

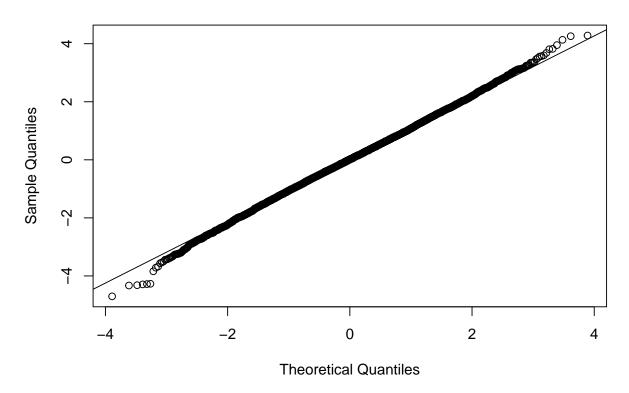
A Small test to see what type of data we want. Can delete

```
nt = 10000
xt = 1.1 + sin(seq(1, 6 * 2 * pi, length.out = nt))/5
rt = rnorm(nt, sd = xt)
par(mfrow = c(1, 1))
plot(rt, type = "l")
lines(xt, col = "cyan")
```



qqnorm(rt)
qqline(rt)

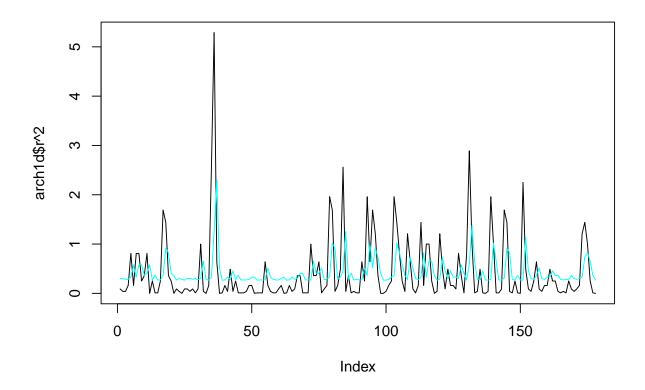
Normal Q-Q Plot



Model selection

```
logLike = function(mod, m = 1) {
    i = (m + 1):(mod\$n) # can burn m first values
    11 = sum(-0.5 * (log(mod$sigmaForecast[i]) + mod$r[i]^2/mod$sigmaForecast[i]))
    return(11)
}
aic = function(mod, m = 1) {
    return(2 * (mod$p + mod$q) - 2 * logLike(mod, m))
}
loglikes = numeric(length(models))
aics = numeric(length(models))
loglikesM = numeric(length(models))
aicsM = numeric(length(models))
for (i in 1:length(models)) {
    loglikes[i] = logLike(models[[i]])
    aics[i] = aic(models[[i]])
    loglikesM[i] = logLike(models[[i]], models[[i]]$m)
```

```
aicsM[i] = aic(models[[i]], models[[i]]$m)
   print(sum(models[[i]]$r^2/models[[i]]$sigmaForecast))
}
## [1] 178.9952
## [1] 178
## [1] 178.9979
## [1] 177.9857
## [1] 184.6648
## [1] 177.6991
## [1] 178.8455
## [1] 177.9982
modSel = cbind(ll = loglikes, llM = loglikesM, aic = aics, aicM = aicsM)
rownames(modSel) = names(models)
modSel
##
                      11
                                11M
                                          aic
                                                   aicM
## arch1regr
              46.4575718 46.4575718 -88.91514 -88.91514
              -4.4729068 -4.4729068 12.94581 12.94581
## arch1d
## arch2regr 47.2728846 46.6138710 -88.54577 -87.22774
## arch2d
              -4.4763785 -5.0084038 14.95276 16.01681
## arch10regr 53.9399839 49.2894127 -85.87997 -76.57883
              -0.6363949 -0.4641352 23.27279 22.92827
## arch10d
## garch12regr 47.3758710 46.4187290 -88.75174 -86.83746
## garch12
              -4.4729649 -5.0043698 14.94593 16.00874
plot(arch1d$r^2, type = "1")
lines(arch1d$sigmaForecast, col = "cyan")
```



sum(arch1d\$r^2/arch1d\$sigmaForecast)

[1] 178

length(arch1d\$sigmaForecast)

[1] 178

```
fgarch = fGarch::garchFit(~garch(1, 0), data = d, trace = F)
fit = fGarch::volatility(fgarch)
fit - arch1d$sigmaForecast
```

```
##
     [1]
          0.35440169
                       0.24922689
                                   0.24183423
                                                0.24856248
                                                             0.23595246
                                                                          0.19512649
##
          0.23595246
     [7]
                       0.17418245
                                    0.19512649
                                                0.23050035
                                                             0.23906245
                                                                          0.17418245
##
    [13]
          0.24540461
                       0.24526913
                                   0.24367574
                                                0.24367574
                                                             0.24526913
                                                                          0.05947873
##
    [19]
          0.07930232
                       0.22231636
                                    0.24526913
                                                0.24540461
                                                             0.23947362
                                                                          0.24856248
                                                             0.24922689
##
    [25]
          0.24540461
                       0.23947362
                                   0.24922689
                                                0.24183423
                                                                          0.24711361
##
          0.24922689
                       0.14832394
                                   0.24856248
                                                0.24540461
                                                             0.23595246 -0.13538916
    [37] -0.75405448
                       0.21458181
                                                                          0.24856248
##
                                   0.24540461
                                                0.24367574
                                                             0.23595246
##
    [43]
          0.21063996
                       0.24183423
                                    0.24526913
                                                0.24367574
                                                             0.24711361
                                                                          0.24711361
    [49]
##
          0.24183423
                       0.23595246
                                   0.24839407
                                                0.24540461
                                                             0.24711361
                                                                          0.24711361
##
    [55]
          0.24711361
                       0.19479056
                                   0.24839407
                                                0.24856248
                                                             0.24711361
                                                                          0.24711361
    [61]
          0.23947362
                       0.23595246
                                   0.24540461
                                                0.24711361
                                                             0.24839407
                                                                          0.24856248
##
```

```
[67] 0.23947362 0.22231636 0.23906245 0.24711361 0.24711361 0.24711361
## [73] 0.14832394 0.23906245 0.22231636 0.21458181 0.24711361 0.24922689
## [79] 0.23595246 -0.01472241 0.05947873 0.24856248 0.24839407
                                                                 0.22904623
0.24711361
   [91] 0.24367574 0.19479056 0.24526913 -0.01472241
                                                     0.21458181
                                                                 0.05947873
## [97] 0.11680841 0.23906245 0.24540461 0.24540461 0.24183423 0.23595246
## [103] 0.24526913 -0.01472241 0.10268116 0.19512649 0.23050035 0.24856248
## [109] 0.11680841 0.21458181 0.23947362 0.24711361
                                                     0.23595246 0.10268116
## [115] 0.23595246 0.14832394 0.17022817 0.23050035 0.24540461
                                                                 0.24856248
## [121] 0.11680841 0.22904623 0.24922689 0.22904623 0.23595246 0.24839407
## [127] 0.23947362 0.17418245 0.23906245 0.24367574
                                                     0.17418245 -0.18058596
## [133] 0.14832394 0.24711361 0.24183423 0.22904623
                                                     0.24711361 0.24540461
## [139] 0.24856248 -0.01472241 0.17022817 0.24367574
                                                     0.24367574 0.24922689
## [145] 0.03553300 0.10268116 0.24183423 0.24711361
                                                      0.24526913 0.24367574
## [151] 0.24540461 -0.07164645 0.22904623 0.24922689
                                                      0.24183423
                                                                 0.24526913
## [157] 0.19479056 0.24922689
                               0.24183423
                                          0.24839407
                                                      0.24839407
                                                                 0.21063996
## [163] 0.24526913 0.23050035 0.24856248 0.24711361
                                                      0.24856248
                                                                 0.24367574
## [169] 0.23050035 0.24922689 0.24183423 0.24922689
                                                      0.24839407
                                                                 0.11680841
## [175] 0.10268116 0.14832394 0.24526913 0.24711361
## attr(,"type")
## [1] "sigma"
sum(d^2/fit^2)
## [1] 178.8808
fGarch::summary(fGarch::garchFit(~garch(1, 0), data = d, trace = F))$show[18]
##
## Title:
   GARCH Modelling
##
  fGarch::garchFit(formula = ~garch(1, 0), data = d, trace = F)
##
## Mean and Variance Equation:
  data ~ garch(1, 0)
## <environment: 0x000002715f53dfc0>
##
   [data = d]
##
## Conditional Distribution:
##
  norm
##
## Coefficient(s):
##
                       alpha1
        mu
               omega
## 0.022472 0.263492 0.395732
##
## Std. Errors:
##
  based on Hessian
##
## Error Analysis:
          Estimate Std. Error t value Pr(>|t|)
## mu
           0.02247
                      0.03790
                                0.593
                                        0.5533
```

```
## omega
           0.26349
                      0.04388
                                6.005 1.91e-09 ***
## alpha1
           0.39573
                      0.15060
                                2.628 0.0086 **
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Log Likelihood:
## -167.3975
               normalized: -0.9404351
##
## Description:
## Fri Nov 17 16:47:39 2023 by user: kikka
##
##
## Standardised Residuals Tests:
##
                                  Statistic
                                                 p-Value
## Jarque-Bera Test R Chi^2
                                  11.2181424 3.664471e-03
## Shapiro-Wilk Test R W
                                  0.9680396 4.171312e-04
## Ljung-Box Test
                  R Q(10)
                                  60.2226812 3.289101e-09
## Ljung-Box Test
                     R
                          Q(15) 118.9905101 0.000000e+00
## Ljung-Box Test
                          Q(20) 148.4393392 0.000000e+00
                     R
                     R^2 Q(10)
## Ljung-Box Test
                                 15.5022697 1.147947e-01
## Ljung-Box Test
                                  28.0330311 2.136318e-02
                     R^2 Q(15)
## Ljung-Box Test
                     R^2 Q(20)
                                  31.2118334 5.245529e-02
## LM Arch Test
                          TR^2
                                  23.7586298 2.193391e-02
## Information Criterion Statistics:
       AIC
               BIC
                        SIC
## 1.914578 1.968204 1.914022 1.936325
## [1] "0.022472 0.263492 0.395732 "
arch1d$estim
```

[1] 0.2681048 0.3845943

Forecasting

```
forecast = function(mod, n) {
    m = mod$m
    p = mod$p
    r = mod$r
    nTot = mod$n + n

alpha = mod$estim[1:(p + 1)]
    if (mod$q == 0)
        {
            beta = 0
            q = 1
        } # If ARCH(p) model

else {
        beta = mod$estim[-(1:(p + 1))]
```

```
q = mod$q
}

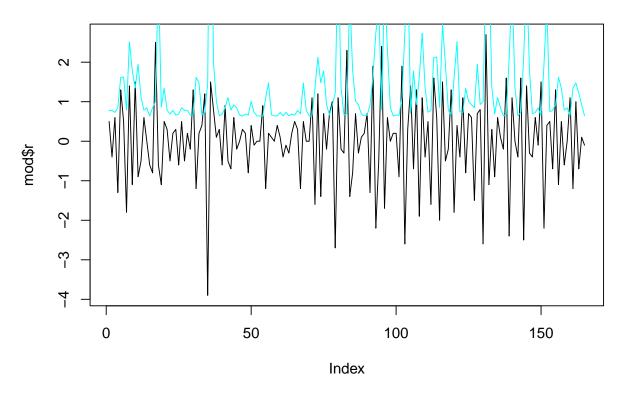
rf = r
length(rf) = nTot
sf = mod$sigmaForecast
length(sf) = nTot
for (t in mod$n:(nTot)) {
    sf[t + 1] = sum(alpha * c(1, rf[(t + 1 - 1):(t + 1 - p)]^2)) + sum(beta *
        sf[(t + 1 - 1):(t + 1 - q)])
    rf[t + 1] = rnorm(1, sd = sqrt(sf[t + 1]))
}
return(rf)
}
```

Fit models without one year

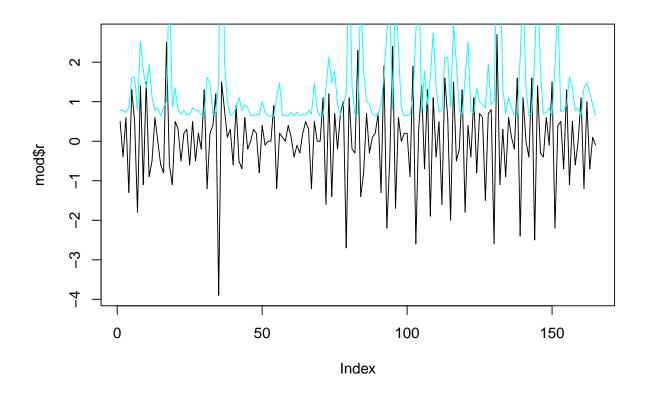
```
# make data to fit
without = 12
dTot = diff(df$Inflation)
nTot = length(dTot)
d = diff(dTot[1:(nTot - without)])

garch12 = Garch(d, p = 1, q = 2, init = rep(0.1, 1 + 2 + 1))
modResults(garch12, "garch(1,2) on diff")
```

garch(1,2) on diff



```
garch12$w = without
garch12$forecast = forecast(garch12, garch12$w)
modResults(garch12)
```



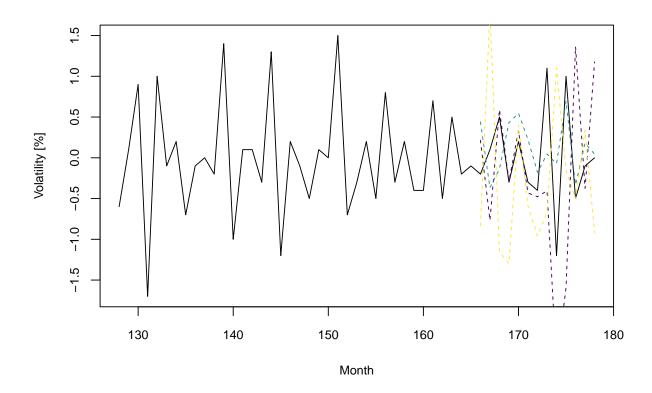
Run all with forecast

```
set.seed(420)
without = 12
dTot = diff(df$Inflation)
nTot = length(dTot)
```

```
d = diff(dTot[1:(nTot - without)])
arch1df = Garch(d, p = 1, q = 0, init = rep(0.1, 2))
arch2df = Garch(d, p = 2, q = 0, init = rep(0.1, 3))
arch10df = Garch(d, p = 10, q = 0, init = rep(0.1, 11))
modelsf = list(arch1df = arch1df, arch2df = arch2df, arch10df = arch10df)
modelsf$arch1df$w = 12
modelsf$arch1df$w
```

[1] 12

```
# for (mod in modelsf){
for (i in 1:length(modelsf)) {
    # browser()
    w = 12
    modelsf[[i]]$w = w
    # mod$w = w
    modelsf[[i]]$forecast = forecast(modelsf[[i]], w)
}
back = 50
plot((nTot - back):nTot, dTot[(nTot - back):nTot], type = "l", xlab = "Month", ylab = "Volatility [%]",
    cex.main = 0.8, cex.axis = 0.8, cex.lab = 0.8)
plotForecast(modelsf)
```



pdf ## 2