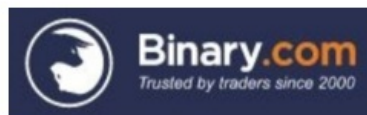


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binary.com 面试题 I - GARCH 模型中的 ARIMA(p,d,q) 参数最优化

by 廖宇, Lian Hu (English)

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1 简介

近几年开始着手汇市预测与投资模式，分别使用了 ARIMA、ETS、GARCH 等等统计模型。在比较了多模型后，GJR-GARCH 预测最为精准，然而在默认模型下并没有将 ARIMA(p,d,q) 值最优化。

原文：哥哥姐姐，请问 IGARCH 模型的参数估计怎么编程实现啊，此文章添加解释与一些参考文献，并且测试 3 年移动数据以确定新 GARCH 模型是否更为精准。

```
suppressPackageStartupMessages(require('BBmisc'))

## 读取程序包
pkg <- c('lubridate', 'plyr', 'dplyr', 'magrittr', 'stringr', 'rugarch', 'forecast', 'quantmod', 'microbenchmark', 'knitr', 'kableExtra', 'formattable')
suppressAll(lib(pkg))
rm(pkg)
```

无意中发下，分享下 rugarch 中的 GARCH 模式最优化...

2 数据

首先读取 Binary.com Interview Q1 (Extension) 的汇市数据。

```
cr_code <- c('AUDUSD=X', 'EURUSD=X', 'GBPUSD=X', 'CHF=X', 'CAD=X', 'CNY=X', 'JPY=X')

# names(cr_code) <- c('AUDUSD', 'EURUSD', 'GBPUSD', 'USDCHF', 'USDCAD', 'USDCNY', 'USDJPY')

names(cr_code) <- c('USDAUD', 'USDEUR', 'USDGBP', 'USDCHF', 'USDCAD', 'USDCNY', 'USDJPY')

price_type <- c('Op', 'Hi', 'Lo', 'Cl')

## 读取雅虎数据。
mbase <- sapply(names(cr_code), function(x) readRDS(paste0('./data/', x, '.rds')))
%>% na.omit()
```

数据简介报告。

```
sapply(mbase, summary) %>%
  kable %>%
  kable_styling(bootstrap_options = c('striped', 'hover', 'condensed', 'responsive')) %>%
  scroll_box(width = '100%', height = '400px')
```

USDAUD	USDEUR	USDGBP	USDCHF	USDCAD	USDCNY	USDJPY
Min.	Min.	Min.	Min.	Min.	Min.	Min.
:2012-01-02	:2012-01-02	:2012-01-02	:2012-01-02	:2012-01-02	:2012-01-02	:2012-01-02
1st Qu.:2013-05-31	1st Qu.:2013-05-31	1st Qu.:2013-05-30	1st Qu.:2013-06-03	1st Qu.:2013-05-30	1st Qu.:2013-05-29	1st Qu.:2013-05-29
Median :2014-10-31	Median :2014-10-31	Median :2014-10-31	Median :2014-11-03	Median :2014-10-30	Median :2014-10-30	Median :2014-10-30
Mean :2014-10-	Mean :2014-10-	Mean :2014-10-	Mean :2014-11-	Mean :2014-10-	Mean :2014-10-	Mean :2014-10-

31	31	30	01	30	30	30
3rd	3rd	3rd	3rd	3rd	3rd	3rd
Qu.:2016-03-30	Qu.:2016-03-30	Qu.:2016-03-30	Qu.:2016-03-31	Qu.:2016-03-29	Qu.:2016-03-30	Qu.:2016-03-30

桌面2.1: 数据简介。

3 统计建模

3.1 基础模型

fGarch : Various submodels arise from this model, and are passed to the ugarchspec “variance.model” list via the submodel option,

- The simple GARCH model of Bollerslev (1986) when $\lambda = \delta = 2$ and $\eta_{1j} = \eta_{2j} = 0$ (submodel = ‘GARCH’).
- The Absolute Value GARCH (AVGARCH) model of Taylor (1986) and Schwert (1990) when $\lambda = \delta = 1$ and $|\eta_{1j}| \leq 1$ (submodel = ‘AVGARCH’).
- The GJR GARCH (GJRGARCH) model of Glosten et al. (1993) when $\lambda = \delta = 2$ and $\eta_{2j} = 0$ (submodel = ‘GJRGARCH’).
- The Threshold GARCH (TGARCH) model of Zakoian (1994) when $\lambda = \delta = 1$, $\eta_{2j} = 0$ and $|\eta_{1j}| \leq 1$ (submodel = ‘TGARCH’).
- The Nonlinear ARCH model of Higgins et al. (1992) when $\delta = \lambda$ and $\eta_{1j} = \eta_{2j} = 0$ (submodel = ‘NGARCH’).
- The Nonlinear Asymmetric GARCH model of Engle and Ng (1993) when $\delta = \lambda = 2$ and $\eta_{1j} = 0$ (submodel = ‘NAGARCH’).
- The Asymmetric Power ARCH model of Ding et al. (1993) when $\delta = \lambda$, $\eta_{2j} = 0$ and $|\eta_{1j}| \leq 1$ (submodel = ‘APARCH’).
- The Exponential GARCH model of Nelson (1991) when $\delta = 1$, $\lambda = 0$ and $\eta_{2j} = 0$ (not implemented as a submodel of fGARCH).
- The Full fGARCH model of Hentschel (1995) when $\delta = \lambda$ (submodel = ‘ALLGARCH’).

The choice of distribution is entered via the ‘distribution.model’ option of the ugarchspec method. The package also implements a set of functions to work with the parameters of these distributions. These are:

- `ddist(distribution = "norm", y, mu = 0, sigma = 1, lambda = -0.5, skew = 1, shape = 5)` . The density (d^*) function.
- `pdist(distribution = "norm", q, mu = 0, sigma = 1, lambda = -0.5, skew = 1, shape = 5)` . The distribution (p^*) function.
- `qdist(distribution = "norm", p, mu = 0, sigma = 1, lambda = -0.5, skew = 1, shape = 5)` . The quantile (q^*) function.
- `rdist(distribution = "norm", n, mu = 0, sigma = 1, lambda = -0.5, skew = 1, shape = 5)` . The sampling (q^*) function.
- `fitdist(distribution = "norm", x, control = list())` . A function for fitting data using any of the included distributions.
- `delomass(distribution = "norm", skew = 1, shape = 5, lambda = -0.5)` .

- `skewness(distribution = "norm", skew = 1, shape = 5, lambda = -0.5)`
The distribution skewness (analytical where possible else by quadrature integration).
- `dkurtosis(distribution = "norm", skew = 1, shape = 5, lambda = -0.5)`
The distribution excess kurtosis (analytical where it exists else by quadrature integration).

The family of APARCH models includes the ARCH and GARCH models, and five other ARCH extensions as special cases:

- ARCH Model of Engle when $\delta = 2$, $\gamma_i = 0$, and $\beta_j = 0$.
- GARCH Model of Bollerslev when $\delta = 2$, and $\gamma_i = 0$.
- TS-GARCH Model of Taylor and Schwert when $\delta = 1$, and $\gamma_i = 0$.
- GJR-GARCH Model of Glosten, Jagannathan, and Runkle when $\delta = 2$.
- T-ARCH Model of Zakoian when $\delta = 1$.
- N-ARCH Model of Higgins and Bera when $\gamma_i = 0$, and $\beta_j = 0$.
- Log-ARCH Model of Geweke and Pentula when $\delta \rightarrow 0$.

原文: [Parameter Estimation of ARMA Models with GARCH/APARCH Errors - An R and SPlus Software Implementation](#) 文献中的 2. Mean and Variance Equation。

有关多种 GARCH 模式比较, 请参考参考文献中的链接 3... 包括比较:

- `auto.arima`
- exponential smoothing models (ETS)
- GARCH (包括 GARCH、eGARCH、iGARCH、fGARCH、gjrgARCH 等模式)
- exponential weighted models

$$\begin{aligned} \sigma_t^2 = & \omega + \sum_{i=1}^p \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \\ \epsilon_t = & \sigma_t \epsilon_t \end{aligned} \quad \text{Equation 3.1.1}$$

在之前的文章已经分别比较多种统计模式, 得知 GJR-GARCH 模型的预测结果最为精准, 以下稍微介绍下平滑移动加权模型。

3.2 ARMA 模型

ARMA Mean Equation: The $ARMA(p, q)$ process of autoregressive order p and moving average order q can be described as

$$x_t = \mu + \sum_{i=1}^p \alpha_i x_{t-i} + \sum_{j=1}^q \beta_j \epsilon_{t-j} + \epsilon_t \quad \text{Equation 3.2.1}$$

以上函数为滑动加权指数, 请参阅以下链接以了解更多详情:

- [Computer Lab Sessions 2&3](#)
- [時間序列分析 - 總體經濟與財務金融之應用 - 定態時間序列 II ARMA 模型](#)
- [Introduction to the rugarch package](#)
- [Parameter Estimation of ARMA Models with GARCH/APARCH Errors - An R and SPlus Software Implementation](#)
- [How to choose the order of a GARCH model?](#)

3.3 GJR-GARCH: ARMA(p,q) 值最优化 (旧程序)

使用极大似然法计算最优 ARMA order 中的 p 值与 q 值, 将原本默认值最优化, 让模型马尔可夫化, 每日的 p 与 q 值最将会使用最佳值... 不包括 d 值。

```
armaSearch <- suppressWarnings(function(data, .method = 'CSS-ML') {
```

```
## I set .method = 'CSS-ML' as default method since the AIC value we got is
## smaller than using method 'ML' while using method 'CSS' facing error.
##
## https://stats.stackexchange.com/questions/209730/fitting-methods-in-arma
## According to the documentation, this is how each method fits the model:
## - CSS minimises the sum of squared residuals.
## - ML maximises the log-likelihood function of the ARIMA model.
## - CSS-ML mixes both methods: first, CSS is run, the starting parameters
##   for the optimization algorithm are set to zeros or to the values given
##   in the optional argument init; then, ML is applied passing the CSS
##   parameter estimates as starting parameter values for the optimization al
gorithm.
```

```
.methods = c('CSS-ML', 'ML', 'CSS')

if(!.method %in% .methods)
  stop(paste('Kindly choose .method among ',
            paste0(.methods, collapse = ', '), '!'))

armacoeff <- data.frame()
for (p in 0:5){
  for (q in 0:5) {
    #data.arma = arima(diff(data), order = c(p, 0, q))
    #'@ data.arma = arima(data, order = c(p, 1, q), method = .method)
    if(.method == 'CSS-ML') {
      data.arma = tryCatch({
        arma = arima(data, order = c(p, 1, q), method = 'CSS-ML')
        mth = 'CSS-ML'
        list(arma, mth)
      }, error = function(e) tryCatch({
        arma = arima(data, order = c(p, 1, q), method = 'ML')
        mth = 'ML'
        list(arma = arma, mth = mth)
      }, error = function(e) {
        arma = arima(data, order = c(p, 1, q), method = 'CSS')
        mth = 'CSS'
        list(arma = arma, mth = mth)
      }))
    } else if(.method == 'ML') {
      data.arma = tryCatch({
        arma = arima(data, order = c(p, 1, q), method = 'ML')
        mth = 'ML'
        list(arma = arma, mth = mth)
      }, error = function(e) tryCatch({
        arma = arima(data, order = c(p, 1, q), method = 'CSS-ML')
        mth = 'CSS-ML'
        list(arma = arma, mth = mth)
      }, error = function(e) {
        arma = arima(data, order = c(p, 1, q), method = 'CSS')
        mth = 'CSS'
        list(arma = arma, mth = mth)
      }))
    } else if(.method == 'CSS') {
      data.arma = tryCatch({
        arma = arima(data, order = c(p, 1, q), method = 'CSS')
        mth = 'CSS'
        list(arma = arma, mth = mth)
      }, error = function(e) tryCatch({
        arma = arima(data, order = c(p, 1, q), method = 'CSS-ML')
        mth = 'CSS-ML'
        list(arma = arma, mth = mth)
      }, error = function(e) {
        arma = arima(data, order = c(p, 1, q), method = 'ML')
        mth = 'ML'
        list(arma = arma, mth = mth)
      }))
    } else {
      stop(paste('Kindly choose .method among ', paste0(.methods, collapse =
', '), '!'))
    }
    names(data.arma) <- c('arma', 'mth')

    #cat('p =', p, ', q =', q, 'AIC =', data.arma$arima$aic, '\n')
    armacoeff <- rbind(armacoeff, c(p, q, data.arma$arima$aic))
  }
}
```



```
## ARMA Modeling寻找AIC值最小的p,q
colnames(armacoef) <- c('p', 'q', 'AIC')
pos <- which(armacoef$AIC == min(armacoef$AIC))
cat(paste0('method = \'', data.arma$smth, '\', the min AIC = ', armacoef$AIC[pos],
          ', p = ', armacoef$p[pos], ', q = ', armacoef$q[pos], '\n'))
return(armacoef)
})
```

然后把以上的函数嵌入以下GARCH模型，将原本固定参数的ARMA值浮动化。

```
calC <- function(mbase, currency = 'JPY=X', ahead = 1, price = 'C1') {

  # Using "memoise" to automatically cache the results
  source('function/filterFX.R')
  source('function/armaSearch.R')
  mbase = suppressWarnings(filterFX(mbase, currency = currency, price = price))

  armaOrder = suppressWarnings(armaSearch(mbase))
  armaOrder %<>% dplyr::filter(AIC == min(AIC)) %>% .[c('p', 'q')] %>% unlist

  spec = ugarchspec(
    variance.model = list(
      model = 'gjrGARCH', garchOrder = c(1, 1),
      submodel = NULL, external.regressors = NULL,
      variance.targeting = FALSE),
    mean.model = list(
      armaOrder = armaOrder,
      include.mean = TRUE, archm = FALSE,
      archpow = 1, arfima = FALSE,
      ## https://stats.stackexchange.com/questions/73351/how-does-one-specify-arima-p-d-q-in-ugarchspec-for-ugarchfit-in-rugarch?answertab=votes#tab-top
      ## https://d.cosx.org/d/2689-2689/9
      external.regressors = NULL,
      archex = FALSE),
    distribution.model = 'snorm')
  fit = ugarchfit(spec, mbase, solver = 'hybrid')
  fc = ugarchforecast(fit, n.ahead = ahead)
  res = tail(attributes(fc)$forecast$seriesFor, 1)
  colnames(res) = names(mbase)
  latestPrice = tail(mbase, 1)

  #rownames(res) <- as.character(forDate)
  latestPrice <- xts(latestPrice)
  #res <- as.xts(res)

  tmp = list(latestPrice = latestPrice, forecastPrice = res,
             AIC = infocriteria(fit))
  return(tmp)
}
```

3.4 Fi-GJR-GARCH: ARFIMA(p,d,q)值最优化 (新程序)

The fractionally integrated GARCH model ('fiGARCH') :

Contrary to the case of the ARFIMA model, the degree of persistence in the FIGARCH model operates in the opposite direction, so that as the fractional differencing parameter d gets closer to one, the memory of the FIGARCH process increases, a direct result of the parameter acting on the squared errors rather than the conditional variance. When $d = 0$ the FIGARCH collapses to the vanilla GARCH model and when $d = 1$ to the integrated GARCH model...

Motivated by the developments in long memory processes, and in particular the ARFIMA type models (see section 2.1), Baillie et al. (1996) proposed the fractionally integrated generalized autoregressive conditional heteroscedasticity, or FIGARCH, model to capture long memory (in essence hyperbolic memory). Unlike the standard GARCH where shocks decay at an

exponential rate, or the integrated GARCH model where shocks persist forever, in the FIGARCH model shocks decay at a slower hyperbolic rate. Consider the standard GARCH equation:

$$\begin{aligned} \sigma_t^2 &= \omega + \alpha(L) \varepsilon_t^2 + \beta(L) \sigma_t^2 \end{aligned} \quad \text{Equation 3.1.2}$$

原文: [Introduction to the rugarch package](#) 文献中的 2.2.10 The fractionally integrated GARCH model ('figARCH')

然后计算最优 arma order... 也包括 d 值。

```
opt_arma <- function(mbase){  
  #ARMA Modeling minimum AIC value of 'p,d,q'  
  fit <- auto.arima(mbase)  
  arimaorder(fit)  
}
```

再来就设置 Garch 模型中的 arfima 参数, 将原本固定的 d 值浮动化。

```
calc_fx <- function(mbase, currency = 'JPY=X', ahead = 1, price = 'C1') {  
  
  ## Using "memoise" to automatically cache the results  
  ## http://rpubs.com/englianhu/arma-order-for-garch  
  source('function/filterFX.R')  
  #'@ source('function/armaSearch.R') #old optimal arma p,q value searching, but no d value.  
  source('function/opt_arma.R') #rename the function best.ARMA()  
  
  mbase = suppressWarnings(filterFX(mbase, currency = currency, price = price))  
  armaOrder = opt_arma(mbase)  
  
  ## Set arma order for 'p, d, q' for GARCH model.  
  #'@ https://stats.stackexchange.com/questions/73351/how-does-one-specify-arima-p-d-q-in-ugarchspec-for-ugarchfit-in-rugarch  
  spec = ugarchspec(  
    variance.model = list(  
      model = 'gjrGARCH', garchOrder = c(1, 1),  
      submodel = NULL, external.regressors = NULL,  
      variance.targeting = FALSE),  
    mean.model = list(  
      armaOrder = armaOrder[c(1, 3)], #set arma order for 'p' and 'q'.  
      include.mean = TRUE, archm = FALSE,  
      archpow = 1, arfima = TRUE, #set arima = TRUE  
      external.regressors = NULL,  
      archex = FALSE),  
    fixed.pars = list(arfima = armaOrder[2]), #set fixed.pars for 'd' value  
    distribution.model = 'snorm')  
  
  fit = ugarchfit(spec, mbase, solver = 'hybrid')  
  
  fc = ugarchforecast(fit, n.ahead = ahead)  
  #res = xts::last(attributes(fc)$forecast$seriesFor)  
  res = tail(attributes(fc)$forecast$seriesFor, 1)  
  colnames(res) = names(mbase)  
  latestPrice = tail(mbase, 1)  
  
  #rownames(res) <- as.character(forDate)  
  latestPrice <- xts(latestPrice)  
  #res <- as.xts(res)  
  
  tmp = list(latestPrice = latestPrice, forecastPrice = res,  
    AIC = infocriteria(fit))  
  return(tmp)  
}
```

4 模式比较

4.1 运行时间

首先比较运行时间, 哪个比较高效。

```
## 测试运行时间。
# '@ microbenchmark(fit <- calc_fx(mbase[[names(cr_code)[sp]]], currency = cr_code[sp]))
# '@ microbenchmark(fit2 <- calc(mbase[[names(cr_code)[sp]]], currency = cr_code[sp]))

## 随机抽样货币数据，测试运行时间。
sp <- sample(1:7, 1)

system.time(fit1 <- calc_fx(mbase[[names(cr_code)[sp]]], currency = cr_code[sp]))
```

```
##      user  system elapsed
## 8.240    0.024   8.382
```

```
system.time(fit2 <- calc(mbase[[names(cr_code)[sp]]], currency = cr_code[sp]))
```

```
## method = 'CSS-ML', the min AIC = -11085.3927792844, p = 5, q = 2
```

```
##      user  system elapsed
## 12.82    0.00   13.61
```

由于使用 `microbenchmark` 非常耗时，而且双方实力悬殊，故此僕使用 `system.time()` 比较运行速度，结果还是新程序 `calc_fx()` 比旧程序 `calc()` 迅速。

4.2 数据误差率

以下僕运行数据测试后事先储存，然后直接读取。首先过滤 `timeID` 时间参数，然后才模拟预测汇价。

```
# '@ lply(mbase, function(x) range(index(x)))
#      .id      V1      V2
#1 USDAUD 2012-01-02 2017-08-30
#2 USDEUR 2012-01-02 2017-08-30
#3 USDCAD 2012-01-02 2017-08-30
#4 USDCNY 2012-01-02 2017-08-30
#5 USDCJPY 2012-01-02 2017-08-30
#6 USDCJPY 2012-01-02 2017-08-30
#7 USDCJPY 2012-01-02 2017-08-30

timeID <- lply(mbase, function(x) as.character(index(x))) %>%
  unlist %>% unique %>% as.Date %>% sort
timeID <- c(timeID, xts::last(timeID) + days(1)) #the last date + 1 in order to predict the next day of last date to make whole dataset completed.
timeID0 <- ymd('2013-01-01')
timeID <- timeID[timeID >= timeID0]

## ----- 6个R进程并行运作 -----
start <- seq(1, length(timeID), ceiling(length(timeID)/6))
#[1] 1 204 407 610 813 1016

stop <- c((start - 1)[-1], length(timeID))
#[1] 203 406 609 812 1015 1217

cat(paste0('\n timeID <- timeID[', paste0(start, ':', stop), ']', '\n')
```

```
##
## timeID <- timeID[1:203]
## timeID <- timeID[204:406]
## timeID <- timeID[407:609]
## timeID <- timeID[610:812]
## timeID <- timeID[813:1015]
## timeID <- timeID[1016:1217]
```

```
#timeID <- timeID[1:203]
#timeID <- timeID[204:406]
#timeID <- timeID[407:609]
#timeID <- timeID[610:812]
#timeID <- timeID[813:1015]
#timeID <- timeID[1016:1217]

## Some currency data doesn't open market in specific date.
#Error:
#data/fx/USDCNY/pred1.2015-04-15.rds saved! #only USDJPY need to review
#data/fx/USDCJPY/pred1.2015-12-07.rds saved! #only USDCJPY need to review
```

```
#data/fx/USDCAD/pred1.2016-08-30.rds saved! #only USDCNY need to review
#data/fx/USDAUD/pred1.2016-11-30.rds saved! #only USDEUR need to review
#data/fx/USDCNY/pred1.2017-01-12.rds saved! #only USDJPY need to review
#data/fx/USDEUR/pred1.2017-02-09.rds saved! #only USGBP need to review
#timeID <- timeID[timeID > ymd('2017-03-08')]

#data/fx/USDCAD/pred2.2015-06-09.rds saved! #only USDCNY need to review
#data/fx/USDCAD/pred2.2015-06-16.rds saved! #only USDCNY need to review
#data/fx/USDCAD/pred2.2015-06-17.rds saved! #only USDCNY need to review
```

模拟 calC() 函数预测汇价数据。

```
## ----- 模拟calC()预测汇价 -----
pred1 <- list()

for (dt in timeID) {

  for (i in seq(cr_code)) {

    smp <- mbase[[names(cr_code)[i]]]
    dtr <- xts::last(index(smp[index(smp) < dt]), 1) #tail(..., 1)
    smp <- smp[paste0(dtr %m-% years(1), '/'), dtr]

    pred1[[i]] <- ldply(price_type, function(y) {
      df = calC(smp, currency = cr_code[i], price = y)
      df = data.frame(Date = index(df[[1]][1]),
                      Type = paste0(names(df[[1]]), '.', y),
                      df[[1]], df[[2]], t(df[[3]]))
      names(df)[4] %<>% str_replace_all('1', 'T+1')
      df
    })

    if (!dir.exists(paste0('data/fx/', names(pred1[[i]])[3])))
      dir.create(paste0('data/fx/', names(pred1[[i]])[3]))

    saveRDS(pred1[[i]], paste0(
      'data/fx/', names(pred1[[i]])[3], '/pred1.',
      unique(pred1[[i]]$Date), '.rds'))

    cat(paste0(
      'data/fx/', names(pred1[[i]])[3], '/pred1.',
      unique(pred1[[i]]$Date), '.rds saved!\n'))

  }; rm(i)
}
```

查询模拟测试进度的函数 task_progress() 如下。

```
task_progress <- function(scs = 60, .pattern = '^pred1', .loops = TRUE) {
  ## ----- 定时查询进度 -----
  ## 每分钟自动查询与更新以上模拟calC()预测汇价进度 (储存文件量)。

  if (.loops == TRUE) {
    while(1) {
      cat('Current Tokyo Time :', as.character(now('Asia/Tokyo')), '\n\n')

      z <- ldply(mbase, function(dtm) {
        y = index(dtm)
        y = y[y >= timeID0]

        cr = as.character(unique(substr(names(dtm), 1, 6)))
        x = list.files(paste0('./data/fx/', cr), pattern = .pattern) %>%
          str_extract_all('[0-9]{4}-[0-9]{2}-[0-9]{2}') %>%
          unlist %>% as.Date %>% sort
        x = x[x >= y[1] & x <= xts::last(y)]

        data.frame(.id = cr, x = length(x), n = length(y)) %>%
          mutate(progress = percent(x/n))
      })# %>% tbl_df

      print(z)

      prg = sum(z$x)/sum(z$n)
      cat('\n===== ', as.character(percent(prg)), '=====\n\n')
    }

    if (prg == 1) break #倘若进度达到100%就停止更新。

    Sys.sleep(scs) #以上ldply()耗时3~5秒。而休息时间60秒。
  }
}
```



```

}
} else {

cat('Current Tokyo Time :', as.character(now('Asia/Tokyo')), '\n\n')

z <- ldply(mbase, function(dtm) {
  y = index(dtm)
  y = y[y >= timeID0]

  cr = as.character(unique(substr(names(dtm), 1, 6)))
  x = list.files(paste0('./data/fx/', cr), pattern = .pattern) %>%
    str_extract_all('[0-9]{4}-[0-9]{2}-[0-9]{2}') %>%
    unlist %>% as.Date %>% sort
  x = x[x >= y[1] & x <= xts::last(y)]

  data.frame(.id = cr, x = length(x), n = length(y)) %>%
    mutate(progress = percent(x/n))
})# %>% tbl_df

print(z)

prg = sum(z$x)/sum(z$n)
cat('\n=====', as.character(percent(prg)), '=====\n\n')
}
}

```

模拟 calc_fx() 函数预测汇价数据。

```

## ----- 模拟calc_fx()预测汇价 -----
pred2 <- list()

for (dt in timeID) {

  for (i in seq(cr_code)) {

    smp <- mbase[[names(cr_code)[i]]]
    dtr <- xts::last(index(smp[index(smp) < dt]), 1) #tail(..., 1)
    smp <- smp[paste0(dtr %m-% years(1), '/'), dtr]

    pred2[[i]] <- ldply(price_type, function(y) {
      df = calc_fx(smp, currency = cr_code[i], price = y)
      df = data.frame(Date = index(df[[1]][1]),
                      Type = paste0(names(df[[1]]), '.', y),
                      df[[1]], df[[2]], t(df[[3]]))
      names(df)[4] %<>% str_replace_all('1', 'T+1')
      df
    })

    if (!dir.exists(paste0('data/fx/', names(pred2[[i]])[3])))
      dir.create(paste0('data/fx/', names(pred2[[i]])[3]))

    saveRDS(pred2[[i]], paste0(
      'data/fx/', names(pred2[[i]])[3], '/pred2.',
      unique(pred2[[i]]$Date), '.rds'))

    cat(paste0(
      'data/fx/', names(pred2[[i]])[3], '/pred2.',
      unique(pred2[[i]]$Date), '.rds saved!\n'))

  }; rm(i)
}

```

模拟完毕后，再来就查看数据结果。

```

## calc()模拟数据误差率
task_progress(.pattern = '^pred1', .loops = FALSE)

```

```

## Current Tokyo Time : 2018-09-07 04:27:06
##
##      .id    x    n progress
## 1 USDAUD 1214 1215   99.92%
## 2 USDEUR 1214 1215   99.92%
## 3 USDBBP 1215 1216   99.92%
## 4 USDCHE 1214 1215   99.92%
## 5 USDCAD 1214 1214  100.00%
## 6 USDCNY 1214 1215   99.92%
## 7 USDJPY 1213 1215   99.84%
...

```

```
##
## ===== 99.92% =====
```

```
## calc_fx() 模拟数据误差率
task_progress(.pattern = '^pred2', .loops = FALSE)
```

```
## Current Tokyo Time : 2018-09-07 04:27:06
##
##      .id      x      n progress
## 1 USDAUD 1215 1215   100.00%
## 2 USDEUR 1215 1215   100.00%
## 3 USDGBP 1216 1216   100.00%
## 4 USDCHF 1215 1215   100.00%
## 5 USDCAD 1214 1214   100.00%
## 6 USDCNY 1212 1215    99.75%
## 7 USDJPY 1215 1215   100.00%
##
## ===== 99.96% =====
```

以上结果显示，模拟后的数据的误差率非常渺小¹。以下筛选 pred1 与 pred2 同样日期的有效数据。

```
##数据1
fx1 <- l1ply(names(cr_code), function(x) {
  fls <- list.files(paste0('data/fx/'), x, pattern = '^pred1')
  dfm <- ldply(fls, function(y) {
    readRDS(paste0('data/fx/', x, '/', y))
  }) %>% data.frame(Cat = 'pred1', .) %>% tbl_df
  names(dfm)[4:5] <- c('Price', 'Price.T1')
  dfm
})
names(fx1) <- names(cr_code)

##数据2
fx2 <- l1ply(names(cr_code), function(x) {
  fls <- list.files(paste0('data/fx/'), x, pattern = '^pred2')
  dfm <- ldply(fls, function(y) {
    readRDS(paste0('data/fx/', x, '/', y))
  }) %>% data.frame(Cat = 'pred2', .) %>% tbl_df
  names(dfm)[4:5] <- c('Price', 'Price.T1')
  dfm
})
names(fx2) <- names(cr_code)

#合并，并且整理数据。
fx1 %>% ldply %>% tbl_df
fx2 %>% ldply %>% tbl_df
fx <- suppressAll(bind_rows(fx1, fx2) %>% arrange(Date) %>%
  mutate(.id = factor(.id), Cat = factor(Cat)) %>%
  ddply(. (Cat, Type), function(x) {
    x %>% mutate(Price.T1 = lag(Price.T1, 1))
  }) %>% tbl_df %>%
  dplyr::filter(Date >= ymd('2013-01-01') & Date <= ymd('2017-08-30')))

rm(fx1, fx2)
```

```
## filter all predictive error where sd >= 20%
notID <- fx %>% mutate(diff = abs(Price.T1/Price), se = ifelse(diff <= 0.8 | diff
>= 1.25, 1, 0)) %>% dplyr::filter(se == 1)
ntimeID <- notID %>% .$Date %>% unique
notID %>%
  kable(caption = 'Error data') %>%
  kable_styling(bootstrap_options = c('striped', 'hover', 'condensed', 'responsiv
e')) %>%
  scroll_box(width = '100%', height = '400px')
```

Error data

.id	Cat	Date	Type	Price	Price.T1	Akaike	Ba
USDCHF	pred1	2015-07-28	USDCHF.Op	0.962	-1674.2440018	-6.855036	-6.691
USDCHF	pred1	2015-01-15	USDCHF.Lo	0.733	1.0165024	-5.799861	-5.718
USDCNY	pred1	2014-	USDCNY.Lo	2.201	6.1863967	-2.713266	-2.631

			07-10				
USDCNY	pred1	2014-07-14	USDCNY.Lo	6.196	1.2948723	-3.150394	-3.013
USDJPY	pred1	2013-06-27	USDJPY.Op	98.468	78.3949808	4.713287	4.795
USDJPY	pred1	2013-06-30	USDJPY.Op	99.411	78.3964420	4.735608	4.817

僕尝试运行好几次，USDCNF 都是获得同样的结果。然后将默认的 snorm 分布更换为 norm 就没有出现错误。至于 USDCNY 原始数据有误就不是统计模型的问题了。

```
fx %<>% dplyr::filter(!Date %in% ntimeID)
```

4.3 精准度

现在就比较下双方的MSE值与AIC值。

```
acc <- ddply(fx, . (Cat, Type), summarise,
  mse = mean((Price.T1 - Price)^2),
  n = length(Price),
  Akaike.mse = (-2*mse)/n+2*4/n,
  Akaike = mean(Akaike),
  Bayes = mean(Bayes),
  Shibata = mean(Shibata),
  Hannan.Quinn = mean(Hannan.Quinn)) %>%
tbl_df %>% mutate(mse = round(mse, 6)) %>%
arrange(Type)

acc %>%
  kable(caption = 'Group Table Summary') %>%
  kable_styling(bootstrap_options = c('striped', 'hover', 'condensed', 'responsive')) %>%
  group_rows('USD/AUD Open', 1, 2, label_row_css = 'background-color: #e68a00; color: #fff;') %>%
  group_rows('USD/AUD High', 3, 4, label_row_css = 'background-color: #e68a00; color: #fff;') %>%
  group_rows('USD/AUD Low', 5, 6, label_row_css = 'background-color: #e68a00; color: #fff;') %>%
  group_rows('USD/AUD Close', 7, 8, label_row_css = 'background-color: #e68a00; color: #fff;') %>%
  group_rows('USD/EUR Open', 9, 10, label_row_css = 'background-color: #6666ff; color: #fff;') %>%
  group_rows('USD/EUR High', 11, 12, label_row_css = 'background-color: #6666ff; color: #fff;') %>%
  group_rows('USD/EUR Low', 13, 14, label_row_css = 'background-color: #6666ff; color: #fff;') %>%
  group_rows('USD/EUR Close', 15, 16, label_row_css = 'background-color: #6666ff; color: #fff;') %>%
  group_rows('USD/GBP Open', 17, 18, label_row_css = 'background-color: #339966; color: #fff;') %>%
  group_rows('USD/GBP High', 19, 20, label_row_css = 'background-color: #339966; color: #fff;') %>%
  group_rows('USD/GBP Low', 21, 22, label_row_css = 'background-color: #339966; color: #fff;') %>%
  group_rows('USD/GBP Close', 23, 24, label_row_css = 'background-color: #339966; color: #fff;') %>%
  group_rows('USD/CHF Open', 25, 26, label_row_css = 'background-color: #808000; color: #fff;') %>%
  group_rows('USD/CHF High', 27, 28, label_row_css = 'background-color: #808000; color: #fff;') %>%
  group_rows('USD/CHF Low', 29, 30, label_row_css = 'background-color: #808000; color: #fff;') %>%
  group_rows('USD/CHF Close', 31, 32, label_row_css = 'background-color: #808000; color: #fff;') %>%
  group_rows('USD/CAD Open', 33, 34, label_row_css = 'background-color: #666; color: #fff;') %>%
  group_rows('USD/CAD High', 35, 36, label_row_css = 'background-color: #666; color: #fff;') %>%
  group_rows('USD/CAD Low', 37, 38, label_row_css = 'background-color: #666; color: #fff;') %>%
  group_rows('USD/CAD Close', 39, 40, label_row_css = 'background-color: #666; color: #fff;') %>%
  group_rows('USD/CNY Open', 41, 42, label_row_css = 'background-color: #e60000; color: #fff;') %>%
```

```

group_rows('USD/CNY High', 43, 44, label_row_css = 'background-color: #e60000; color: #fff;') %>%
group_rows('USD/CNY Low', 45, 46, label_row_css = 'background-color: #e60000; color: #fff;') %>%
group_rows('USD/CNY Close', 47, 48, label_row_css = 'background-color: #e60000; color: #fff;') %>%
group_rows('USD/JPY Open', 49, 50, label_row_css = 'background-color: #ff3377; color: #fff;') %>%
group_rows('USD/JPY High', 51, 52, label_row_css = 'background-color: #ff3377; color: #fff;') %>%
group_rows('USD/JPY Low', 53, 54, label_row_css = 'background-color: #ff3377; color: #fff;') %>%
group_rows('USD/JPY Close', 55, 56, label_row_css = 'background-color: #ff3377; color: #fff;') %>%
scroll_box(width = '100%', height = '400px')

```

Group Table Summary

Cat	Type	mse	n	Akaike.mse	Akaike	Bayes
USD/AUD Open						
pred1	USDAUD.Op	0.001274	1198	0.0066757	-6.301423	-6.179739 -6
pred2	USDAUD.Op	0.000063	1199	0.0066721	-7.012446	-6.918191 -7
USD/AUD High						
pred1	USDAUD.Hi	0.002386	1198	0.0066738	-6.340293	-6.212693 -6
pred2	USDAUD.Hi	0.000053	1199	0.0066721	-7.173989	-7.082896 -7
USD/AUD Low						
pred1	USDAUD.Lo	0.002708	1198	0.0066733	-6.547461	-6.420249 -6
pred2	USDAUD.Lo	0.000055	1199	0.0066721	-7.185559	-7.093040 -7
USD/AUD Close						
pred1	USDAUD.Cl	0.001563	1198	0.0066752	-6.234604	-6.113974 -6
pred2	USDAUD.Cl	0.000063	1199	0.0066721	-7.024069	-6.930099 -7
USD/EUR Open						
pred1	USDEUR.Op	0.000394	1198	0.0066771	-7.457792	-7.323364 -7
pred2	USDEUR.Op	0.000023	1199	0.0066722	-8.042653	-7.947164 -8
USD/EUR High						
pred1	USDEUR.Hi	0.000655	1198	0.0066767	-7.317925	-7.189982 -7
pred2	USDEUR.Hi	0.000019	1199	0.0066722	-8.232722	-8.137733 -8
USD/EUR Low						
pred1	USDEUR.Lo	0.000195	1198	0.0066775	-7.903763	-7.761214 -7
pred2	USDEUR.Lo	0.000020	1199	0.0066722	-8.201486	-8.106294 -8
USD/EUR Close						
pred1	USDEUR.Cl	0.000514	1198	0.0066769	-7.473283	-7.338388 -7
pred2	USDEUR.Cl	0.000023	1199	0.0066722	-8.048744	-7.953187 -8
USD/GBP Open						
pred1	USDGBP.Op	0.000142	1199	0.0066720	-8.182935	-8.042463 -8
pred2	USDGBP.Op	0.000017	1200	0.0066666	-8.586886	-8.486623 -8
USD/GBP High						
pred1	USDGBP.Hi	0.000583	1199	0.0066713	-7.432342	-7.315975 -7
pred2	USDGBP.Hi	0.000018	1200	0.0066666	-8.694381	-8.598574 -8
USD/GBP Low						
pred1	USDGBP.Lo	0.000485	1199	0.0066714	-7.830042	-7.705369 -7
pred2	USDGBP.Lo	0.000014	1200	0.0066666	-8.775406	-8.678905 -8
USD/GBP Close						
pred1	USDGBP.Cl	0.000171	1199	0.0066710	-7.888500	-7.755511 -7
pred2	USDGBP.Cl	0.000014	1200	0.0066666	-8.775406	-8.678905 -8

pred1	USDGBP.Cl	0.000171	1199	0.0066719	-7.989503	-7.856511	-7
pred2	USDGBP.Cl	0.000017	1200	0.0066666	-8.598422	-8.501629	-8
USD/CHF Open							
pred1	USDCHF.Op	0.000168	1198	0.0066775	-7.279423	-7.134686	-7
pred2	USDCHF.Op	0.000050	1199	0.0066721	-7.582237	-7.489545	-7
USD/CHF High							
pred1	USDCHF.Hi	0.000627	1198	0.0066767	-7.227931	-7.088508	-7
pred2	USDCHF.Hi	0.000040	1199	0.0066722	-7.754225	-7.658153	-7
USD/CHF Low							
pred1	USDCHF.Lo	0.000468	1198	0.0066770	-6.926481	-6.805613	-6
pred2	USDCHF.Lo	0.000040	1199	0.0066722	-7.738710	-7.645220	-7
USD/CHF Close							
pred1	USDCHF.Cl	0.000174	1198	0.0066775	-7.264507	-7.120544	-7
pred2	USDCHF.Cl	0.000050	1199	0.0066721	-7.592242	-7.498773	-7
USD/CAD Open							
pred1	USDCAD.Op	0.001154	1198	0.0066759	-7.286889	-7.143830	-7
pred2	USDCAD.Op	0.000036	1198	0.0066777	-7.644158	-7.550256	-7
USD/CAD High							
pred1	USDCAD.Hi	0.000318	1198	0.0066773	-7.415677	-7.268040	-7
pred2	USDCAD.Hi	0.000035	1198	0.0066777	-7.788824	-7.686317	-7
USD/CAD Low							
pred1	USDCAD.Lo	0.001628	1198	0.0066751	-7.128295	-6.984931	-7
pred2	USDCAD.Lo	0.000033	1198	0.0066777	-7.727436	-7.634900	-7
USD/CAD Close							
pred1	USDCAD.Cl	0.000842	1198	0.0066764	-7.322163	-7.179071	-7
pred2	USDCAD.Cl	0.000036	1198	0.0066777	-7.657723	-7.563331	-7
USD/CNY Open							
pred1	USDCNY.Op	0.003605	1198	0.0066718	-5.623307	-5.483820	-5
pred2	USDCNY.Op	0.000952	1196	0.0066874	-6.225365	-6.125404	-6
USD/CNY High							
pred1	USDCNY.Hi	0.004772	1198	0.0066698	-5.691631	-5.548543	-5
pred2	USDCNY.Hi	0.000797	1196	0.0066876	-5.996404	-5.890569	-5
USD/CNY Low							
pred1	USDCNY.Lo	0.009417	1198	0.0066621	-5.443779	-5.312434	-5
pred2	USDCNY.Lo	0.000654	1196	0.0066879	-6.049603	-5.952151	-6
USD/CNY Close							
pred1	USDCNY.Cl	0.002597	1198	0.0066735	-5.827701	-5.684826	-5
pred2	USDCNY.Cl	0.000179	1196	0.0066887	-6.479687	-6.374567	-6
USD/JPY Open							
pred1	USDJPY.Op	2.293032	1197	0.0028521	1.963654	2.126971	1
pred2	USDJPY.Op	0.487469	1199	0.0058591	1.883213	1.982120	1
USD/JPY High							
pred1	USDJPY.Hi	4.525426	1197	-0.0008779	2.076003	2.216800	2
pred2	USDJPY.Hi	0.383391	1199	0.0060327	1.642211	1.744885	1
USD/JPY Low							
pred1	USDJPY.Lo	15.012245	1197	-0.0183997	2.253442	2.402294	2
pred2	USDJPY.Lo	0.489058	1199	0.0058565	1.805986	1.900808	1

USD/JPY Close							
pred1	USDJPY.Cl	1.483917	1197	0.0042040	1.941265	2.106190	1
pred2	USDJPY.Cl	0.489430	1199	0.0058558	1.891071	1.990012	1

```

acc <- ddply(fx, .(Cat, .id), summarise,
  mse = mean((Price.T1 - Price)^2),
  n = length(Price),
  Akaike.mse = (-2*mse)/n+2*4/n,
  Akaike = mean(Akaike),
  Bayes = mean(Bayes),
  Shibata = mean(Shibata),
  Hannan.Quinn = mean(Hannan.Quinn)) %>%
tbl_df %>% mutate(mse = round(mse, 6)) %>%
arrange(.id)

acc %>%
  kable(caption = 'Group Table Summary') %>%
  kable_styling(bootstrap_options = c('striped', 'hover', 'condensed', 'responsive')) %>%
  group_rows('USD/AUD', 1, 2, label_row_css = 'background-color: #003399; color: #fff;') %>%
  group_rows('USD/CAD', 3, 4, label_row_css = 'background-color: #003399; color: #fff;') %>%
  group_rows('USD/CHF', 5, 6, label_row_css = 'background-color: #003399; color: #fff;') %>%
  group_rows('USD/CNY', 7, 8, label_row_css = 'background-color: #003399; color: #fff;') %>%
  group_rows('USD/EUR', 9, 10, label_row_css = 'background-color: #003399; color: #fff;') %>%
  group_rows('USD/GBP', 11, 12, label_row_css = 'background-color: #003399; color: #fff;') %>%
  group_rows('USD/JPY', 13, 14, label_row_css = 'background-color: #003399; color: #fff;') %>%
  scroll_box(width = '100%', height = '400px')

```

Group Table Summary							
Cat	.id	mse	n	Akaike.mse	Akaike	Bayes	Shib
USD/AUD							
pred1	USDAUD	0.001983	4792	0.0016686	-6.355945	-6.231664	-6.3581
pred2	USDAUD	0.000059	4796	0.0016680	-7.099016	-7.006056	-7.1001
USD/CAD							
pred1	USDCAD	0.000985	4792	0.0016690	-7.288256	-7.143968	-7.2910
pred2	USDCAD	0.000035	4792	0.0016694	-7.704535	-7.608701	-7.7051
USD/CHF							
pred1	USDCHF	0.000359	4792	0.0016693	-7.174586	-7.037338	-7.1770
pred2	USDCHF	0.000045	4796	0.0016680	-7.666853	-7.572923	-7.6681
USD/CNY							
pred1	USDCNY	0.005098	4792	0.0016673	-5.646605	-5.507406	-5.6490
pred2	USDCNY	0.000646	4784	0.0016720	-6.187765	-6.085673	-6.1890
USD/EUR							
pred1	USDEUR	0.000439	4792	0.0016693	-7.538191	-7.403237	-7.5410
pred2	USDEUR	0.000021	4796	0.0016680	-8.131401	-8.036095	-8.1321
USD/GBP							
pred1	USDGBP	0.000345	4796	0.0016679	-7.858706	-7.730079	-7.8610
pred2	USDGBP	0.000017	4800	0.0016667	-8.663774	-8.566433	-8.6650
USD/JPY							
pred1	USDJPY	5.828655	4788	-0.0007638	2.058591	2.213064	2.0540
pred2	USDJPY	0.462337	4796	0.0014753	1.805620	1.904456	1.8040

```
acc <- ddply(fx, .(Cat), summarise,
  mse = mean((Price.T1 - Price)^2),
  n = length(Price),
  Akaike.mse = (-2*mse)/n+2*4/n,
  Akaike = mean(Akaike),
  Bayes = mean(Bayes),
  Shibata = mean(Shibata),
  Hannan.Quinn = mean(Hannan.Quinn)) %>%
tbl_df %>% mutate(mse = round(mse, 6))

acc %>%
  kable(caption = 'Group Table Summary') %>%
  kable_styling(bootstrap_options = c('striped', 'hover', 'condensed', 'responsive'))
```

Group Table Summary

Cat	mse	n	Akaike.mse	Akaike	Bayes	Shibata	Hannan.Quinn
pred1	0.833286	33544	0.0001888	-5.687425	-5.549847	-5.690497	-5.632126
pred2	0.066189	33560	0.0002344	-6.235520	-6.138908	-6.236992	-6.196687

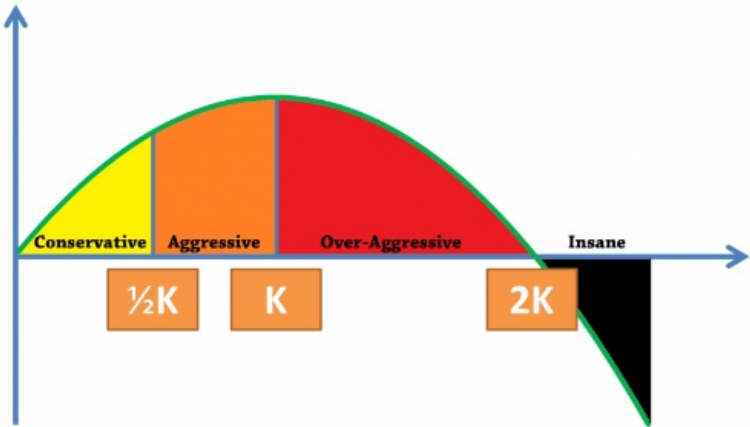
5 结论

结果新的Fi-gjrGARCH函数pred2胜出，比旧的gjrGARCH的pred1更优秀，证明p值、d值与q值仨都可以优化。目前正在编写着Q1App2自动交易应用。“商场如战场”，除了模式最优化以外，程序运作上分秒必争... microbenchmark 测试效率，之前编写了个DataCollection应用采集实时数据以方便之后的高频率交易自动化建模²。欲知更多详情，请参阅Real Time FXCM。

Generalised Autoregressive Conditional Heteroskedasticity GARCH(p, q) Models for Time Series Analysis:

- Discrete White Noise and Random Walks
- AR(p)
- MA(q)
- ARMA(p,q)
- ARIMA(p,d,q)

投注模式



除此之外，由于 $k=\frac{1}{2}$ 凯里模式开始时期的增长率比 $k=1$ 高，故此k值可设置为 $0.5 \leq k \leq 1$ 。Application of Kelly Criterion model in Sportsbook Investment科研也将着手于凯里模式中的k值浮动化。

6 附录

6.1 文件与系统资讯

以下乃此文献资讯：


- 文件建立日期：2018-08-07
- 文件最新更新日期：2018-09-07
- R version 3.4.4 (2018-03-15)
- R语言版本：3.4.4

- [rmarkdown](#) chéng xù bāo 程序包版本: 1.10.8
- 文件版本: 1.0.1
- 作者简历: [@y0](#), Eng Lian Hu
- GitHub: [源代码](#)
- 其它系统资讯:

System Summary

Category	session_info	Category	Sys.info
version	R version 3.4.4 (2018-03-15)	sysname	Linux
system	x86_64, linux-gnu	release	4.4.0-111-generic
ui	X11	version	#134~14.04.1-Ubuntu SMP Mon Jan 15 15:39:56 UTC 2018
language	(EN)	nodename	4b21bf3ded14
collate	C.UTF-8	machine	x86_64
tz	Etc/UTC	login	unknown
date	2018-09-06	user	rstudio-user
Current time	2018-09-07 04:27:37 JST	effective_user	rstudio-user

6.2 cān kǎo wén xiàn 参考文献

1. [How does one specify arima \(p,d,q\) in ugarchspec for ugarchfit in rugarch?](#) 
2. [How to read p,d and q of auto.arima\(\)](#)?
3. [binary.com](#) : Job Application - Quantitative Analyst

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1. yí xiē shù jù 一些数据模拟时, chū xiàn bù zhī míng cuò wù 出现不知名错误。↩
2. bù guò shù jù liàng duō jiù huì dāng jī 不过数据量多就会当机, de jì xù tí shēng cái xíng 得继续提升才行。↩