

621__Homework 4

Litng Hu

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Question 1

1

```
require(Sim.DiffProc)
setwd("/Users/apple/Desktop/621/HW4")
sample_data <- read.csv("sample_data.csv") # Read data
sample_data <- ts(sample_data, deltat=1/365) # dt = 1/365
head(sample_data)

##          stock1    stock2    stock3    stock4    stock5
## [1,] 100.00000 100.00000 100.00000 100.00000 100.0000
## [2,] 100.02068  99.99415 100.04909  99.92849 100.1941
## [3,] 100.02660 100.01964  99.94416  99.92583 100.4359
## [4,] 100.00023 100.07849  99.94365  99.96918 100.4597
## [5,] 100.00754 100.13089  99.87517  99.93167 100.4614
## [6,]  99.96268 100.15621  99.91428  99.96727 100.3518

model.match <- as.data.frame(matrix(nrow = 5, ncol = 2))
model.match[, 1] <- colnames(sample_data)
best.n <- c()
for (i in 1:5) {
  # model 1
  fx1 <- expression( theta[1]*x )
  gx1 <- expression( theta[2]*x^theta[3] )
  mod1 <- fitsde(data=sample_data[, i], drift=fx1, diffusion=gx1,
                 start = list(theta1=1, theta2=1, theta3=1), pmle="euler")

  # model 2
  fx2 <- expression( theta[1]+theta[2]*x )
  gx2 <- expression( theta[3]*x^theta[4] )
  mod2 <- fitsde(data=sample_data[, i], drift=fx2, diffusion=gx2,
                 start = list(theta1=1,theta2=1,theta3=1,theta4=1), pmle="euler")
}
```

```

# model 3
fx3 <- expression( theta[1]+theta[2]*x )
gx3 <- expression( theta[3]*sqrt(x) )
mod3 <- fitsde(data=sample_data[, i], drift=fx3, diffusion=gx3,
               start = list(theta1=1,theta2=1,theta3=1), pmle="euler")

# model 4
fx4 <- expression( theta[1] )
gx4 <- expression( theta[2]*x^theta[3] )
mod4 <- fitsde(data = sample_data[, i], drift=fx4, diffusion=gx4,
               start = list(theta1=1,theta2=1,theta3=1), pmle="euler")

# model 5
fx5 <- expression( theta[1]*x )
gx5 <- expression( theta[2]+theta[3]*x^theta[4] )
mod5 <- fitsde(data=sample_data[, i], drift=fx5, diffusion=gx5,
               start = list(theta1=1,theta2=1,theta3=1,theta4=1), pmle="euler")

# Computes AIC
AIC <- c(AIC(mod1),AIC(mod2),AIC(mod3),AIC(mod4),AIC(mod5))
k <- which.min(AIC) # Choose the minimum
best.n[i] <- k
best <- paste0("model", k)
model.match[i, 2] <- best
}

knitr::kable(model.match, caption = "Model match")

```

Table 1: Model match

V1	V2
stock1	model1
stock2	model1
stock3	model1
stock4	model5
stock5	model1
The best	models are chosen as Model 1,1,1,5,1 respectively based on AIC.

2

```

fx <- list(fx1, fx2, fx3, fx4, fx5)
gx <- list(gx1, gx2, gx3, gx4, gx5)
pmle <- eval(formals(fitsde.default)$pmle)

for (j in 1:5) {
  fitres <- lapply(1:4, function(i) fitsde(data = sample_data[, j], drift=fx[[best.n[j]]], diffusion=
                                           pmle=pmle[i], start=list(theta1=1,theta2=1,theta3=1,theta4=
Coef <- data.frame(do.call("cbind", lapply(1:4, function(i) coef(fitres[[i]]))))
Info <- data.frame(do.call("rbind", lapply(1:4, function(i) logLik(fitres[[i]]))),
                  do.call("rbind", lapply(1:4, function(i) AIC(fitres[[i]]))),
                  do.call("rbind", lapply(1:4, function(i) BIC(fitres[[i]]))))
  Info <- t(Info)
}

```

```

colnames(Coef) <- pmle
colnames(Info) <- pmle
rownames(Info) <- c("logLic", "AIC", "BIC")
result <- rbind(Coef, Info)
print(paste0("stock", j))
print(result)
}

## [1] "stock1"
##          euler      kessler      ozaki      shoji
## theta1  8.062477e-03  0.6357041  8.076304e-03  8.076296e-03
## theta2  4.298704e-02  0.4524182  4.348005e-02  4.348007e-02
## theta3  5.972266e-01 -1.2589008  5.952456e-01  5.952455e-01
## theta4  1.000000e+00  1.0000000  1.000000e+00  1.000000e+00
## logLic  1.281996e+05  0.0000000  1.281988e+05  1.281988e+05
## AIC     -2.563912e+05  8.0000000 -2.563895e+05 -2.563895e+05
## BIC     -2.563762e+05  23.0258709 -2.563745e+05 -2.563745e+05
## [1] "stock2"
##          euler      kessler      ozaki      shoji
## theta1  6.693138e-03  7.186735e-03  6.767031e-03  6.731218e-03
## theta2  3.173901e-02  3.107624e-02  3.199115e-02  3.198999e-02
## theta3  7.902994e-01  7.945091e-01  7.891739e-01  7.891783e-01
## theta4  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
## logLic  6.480208e+04  6.480452e+04  6.480113e+04  6.480115e+04
## AIC     -1.295962e+05 -1.296010e+05 -1.295943e+05 -1.295943e+05
## BIC     -1.295811e+05 -1.295860e+05 -1.295792e+05 -1.295793e+05
## [1] "stock3"
##          euler      kessler      ozaki      shoji
## theta1 -6.447688  0.6908933  7.585487e-03  7.720217e-03
## theta2 -1.240025  0.4878146 -1.121560e-02 -1.128753e-02
## theta3 -1.037941 -1.1314202  1.092039e+00  1.089914e+00
## theta4  1.000000  1.0000000  1.000000e+00  1.000000e+00
## logLic  0.000000  0.0000000 -1.499991e+04 -1.501172e+04
## AIC      8.000000  8.0000000  3.000783e+04  3.003145e+04
## BIC     23.025871  23.0258709  3.002285e+04  3.004648e+04
## [1] "stock4"
##          euler      kessler      ozaki      shoji
## theta1  3.501537e-03  3.620323e-03  3.547551e-03  3.499592e-03
## theta2 -3.106228e-01 -3.392665e-01 -3.626354e-01 -3.642739e-01
## theta3  8.066213e-02  8.523160e-02  8.853891e-02  8.862773e-02
## theta4  6.962709e-01  6.874293e-01  6.816353e-01  6.816288e-01
## logLic  6.525241e+04  6.525224e+04  6.525221e+04  6.525222e+04
## AIC     -1.304968e+05 -1.304965e+05 -1.304964e+05 -1.304964e+05
## BIC     -1.304818e+05 -1.304815e+05 -1.304814e+05 -1.304814e+05
## [1] "stock5"
##          euler      kessler      ozaki      shoji
## theta1  6.347047e-03  5.134631e-03  6.294413e-03  6.336781e-03
## theta2  4.494081e-02  4.444700e-02  4.513493e-02  4.507670e-02
## theta3  7.893863e-01  7.911148e-01  7.884441e-01  7.888489e-01
## theta4  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
## logLic  2.721819e+04  2.721769e+04  2.721773e+04  2.721795e+04
## AIC     -5.442838e+04 -5.442737e+04 -5.442746e+04 -5.442790e+04
## BIC     -5.441336e+04 -5.441234e+04 -5.441243e+04 -5.441287e+04

```

For stock 1, the minimum AIC and BIC appear in euler method. Those calculated by kessler method are much larger ($8 \gg -2.563912e+05$, $23.0258709 \gg -2.563762e+05$).

For stock 2, the minimum AIC and BIC appear in kessler method. And euler's AIC and BIC are also less than ozaki's and shoji's.

For stock 3, the minimum AICs and BICs appear in euler and kessler methods which are much smaller than ozaki's and shoji's.

For stock 4, the minimum AIC and BIC appear in euler method. And kessler's AIC and BIC are also less than ozaki's and shoji's.

For stock 5, the minimum AIC and BIC appear in euler method. And kessler's AIC and BIC are also less than ozaki's and shoji's. (similar situation as stock 4)

3

For my opinion, the Euler method and Kessler method provide best estimates.

Question 2

```
library(xlsx)
swaptions <- read.xlsx("2017_2_15_mid.xlsx", sheetName = "Quotes") # Read data
head(swaptions)
```

```
##   Expiry    NA.  X1Yr  X2Yr  X3Yr  X4Yr  X5Yr  X7Yr  X10Yr  X12Yr  X15Yr
## 1    1Mo    Vol 28.79 44.15 41.98 65.02 70.63 75.92 72.92 73.68 73.57
## 2   <NA> Strike 1.37 1.62 1.83 1.98 2.10 2.27 2.44 2.52 2.60
## 3    3Mo    Vol 42.91 53.08 65.36 74.23 68.76 76.72 81.33 80.44 77.75
## 4   <NA> Strike 1.47 1.71 1.90 2.04 2.15 2.32 2.48 2.55 2.62
## 5    6Mo    Vol 42.71 58.20 67.08 75.01 80.60 83.30 84.40 83.64 81.40
## 6   <NA> Strike 1.61 1.82 2.00 2.12 2.22 2.37 2.52 2.59 2.65
##   X20Yr X25Yr X30Yr
## 1 73.12 72.41 71.92
## 2  2.66  2.68  2.68
## 3 77.47 77.17 76.83
## 4  2.68  2.69  2.69
## 5 84.39 81.52 81.19
## 6  2.70  2.71  2.71
```

```
column <- 5 # choose 5th maturity which is 5 years
dim(swaptions)
```

```
## [1] 38 14
```

```
Vol <- swaptions[seq(1, 38, by=2), 7]/100 # At-the-money volatility
Strike <- swaptions[seq(2, 38, by=2), 7]/100 # Strike price K
expiry <- swaptions[seq(1, 38, by=2), 1] # expiration date

temp <- gregexpr("[0-9]+", expiry)
expiry <- as.numeric(unlist(regmatches(expiry, temp)))
expiry[1:4] <- expiry[1:4]/12 # Expiry date for swaptions
```

1

```
SABRVol<-function(alpha,beta,rho,nu,Tm,f){
  # All the contracts are at the money, so f=K
  Term1 <- alpha/f^(1-beta)
  Term2 <- (1-beta)^2/24*alpha^2/f^(2-2*beta)+rho*beta*nu*alpha/4/f^(1-beta)+(2-3*rho^2)*nu^2/24
  ans <- Term1*(1 + Term2*Tm)
  return(ans)
}

optimization <- function(beta) {
  init.values = c(0.1, 0, 0.1)
  lower.bound = c(0.0001, -1, 0.0001) # -1 < rho < 1
  upper.bound = c(Inf, 1, Inf)

  objective.f <- function(parm,beta) {
    # Objective function
    # to search the minimum sum of (sigma_mkt - sigma_B)^2
    alpha <- parm[1]
    rho <- parm[2]
    nu <- parm[3]
    Sigma_B <- SABRVol(alpha,beta,rho,nu,expiry,Strike)
    return(sum((Vol-Sigma_B)^2))
  }

  # PORT optimization routine
  opt<-nlminb(start=init.values,
             objective = objective.f,
             lower = lower.bound,
             upper = upper.bound,
             beta=beta)

  parms <-opt$par
  obj <- opt$objective
  ans <- t(as.data.frame(c(beta, parms, obj)))
  colnames(ans) <- c("beta", "alpha", "rho", "nu", "objective")
  rownames(ans) <- NULL
  return(ans)
}

re1 <- optimization(0.5)

knitr::kable(re1, caption = "Beta=0.5")
```

Table 2: Beta=0.5

beta	alpha	rho	nu	objective
0.5	0.1278108	-0.7087668	3.214501	0.1607094

2

```
re2 <- optimization(0.7)
re3 <- optimization(0.4)
```

```
knitr::kable(re2, caption = "Beta=0.7")
```

Table 3: Beta=0.7

beta	alpha	rho	nu	objective
0.7	0.2701053	-0.6340573	2.601383	0.1253063

```
knitr::kable(re3, caption = "Beta=0.4")
```

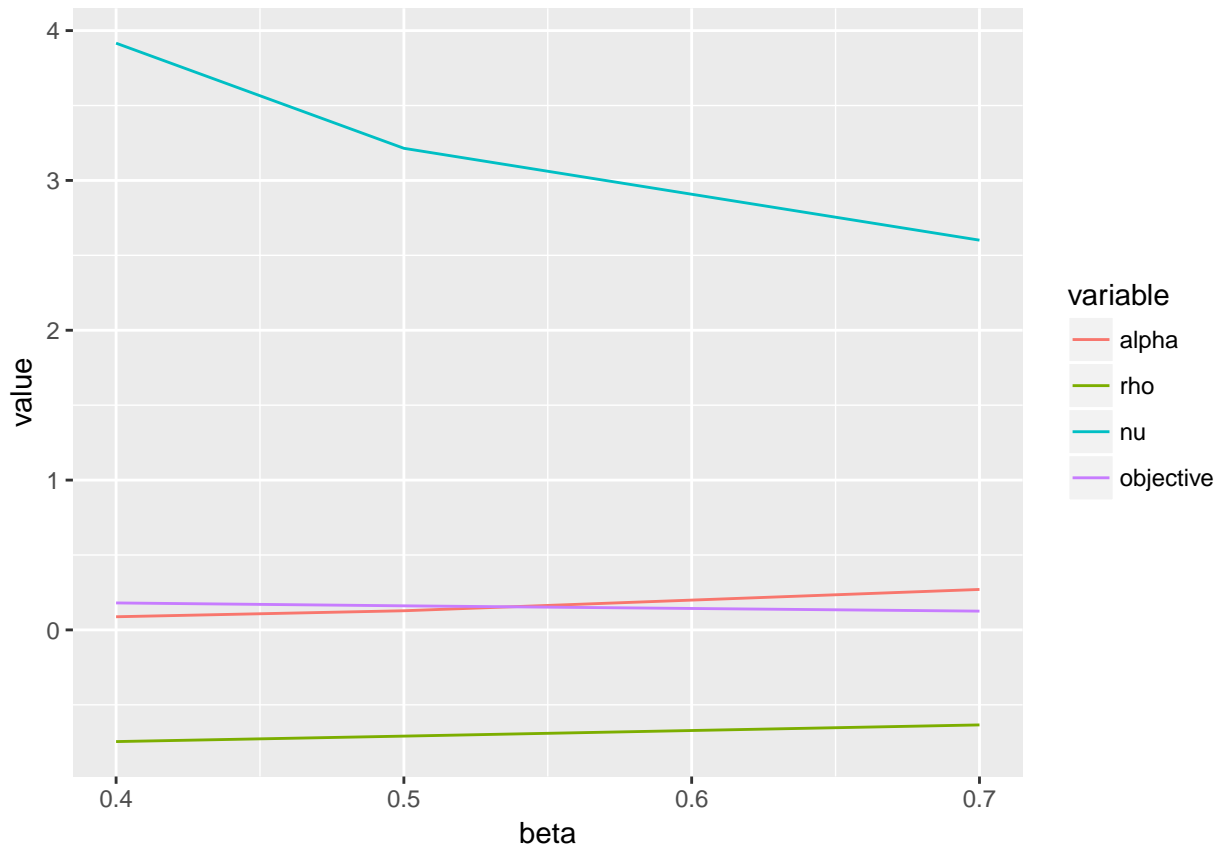
Table 4: Beta=0.4

beta	alpha	rho	nu	objective
0.4	0.0878855	-0.7454043	3.915984	0.1800368

3

```
library(ggplot2)
library(reshape2)
res <- as.data.frame(rbind(re1, re2, re3))

res.long <- melt(res, id="beta")
ggplot(data=res.long, aes(x=beta, y=value, color=variable)) + geom_line()
```



From this plot, we can see that as beta (3 values) grows larger, the objective function decreases. While in the mean time, alpha and rho is getting larger. Nu is decreasing.

4

```
betas <- seq(0, 1, by=0.1)
opts <- optimization(0)
for (i in betas) {
  a <- optimization(i)
  opts <- rbind(opts, a)
}

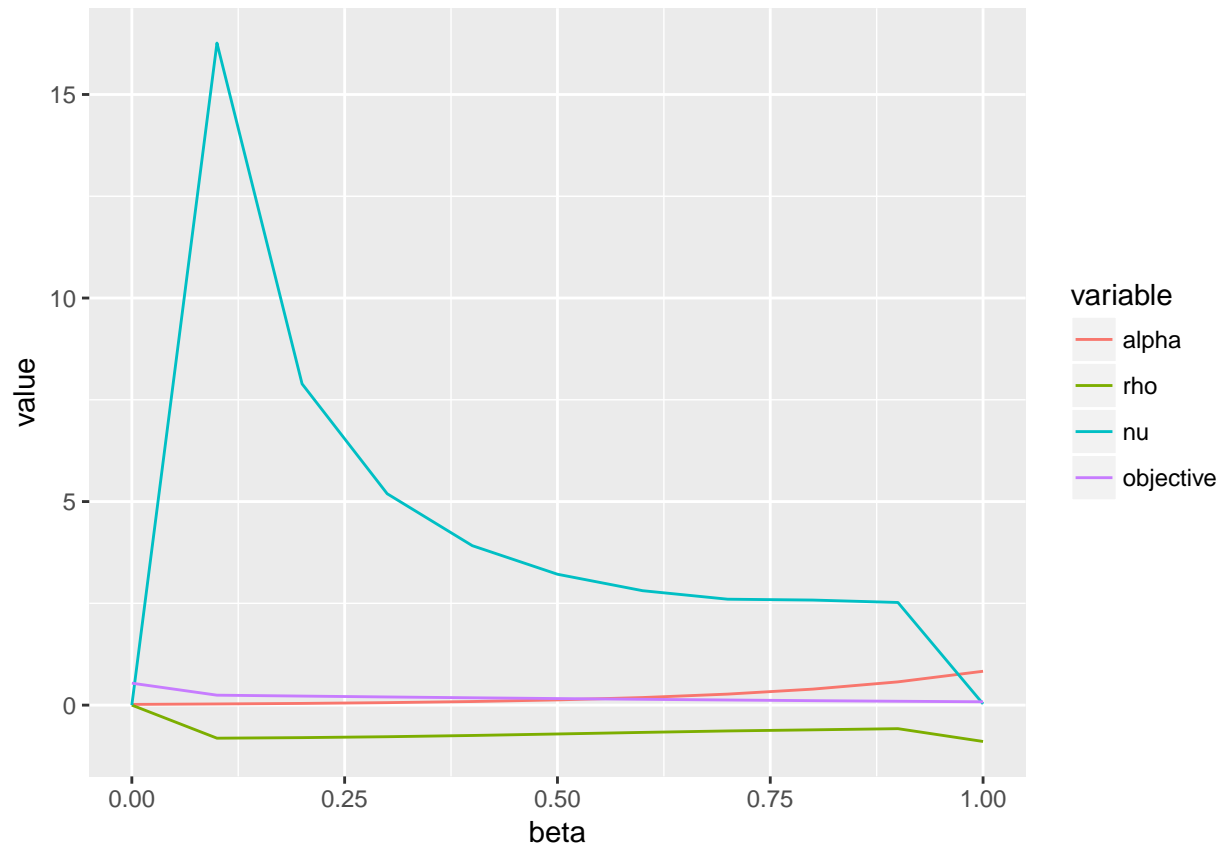
opts <- as.data.frame(opts[2:12, ])

knitr::kable(opts)
```

beta	alpha	rho	nu	objective
0.0	0.0175400	0.0000000	0.0001000	0.5388539
0.1	0.0285304	-0.8123266	16.2623907	0.2441848
0.2	0.0415228	-0.7990391	7.8908936	0.2218027
0.3	0.0604166	-0.7763493	5.1921226	0.2004107
0.4	0.0878855	-0.7454043	3.9159839	0.1800368
0.5	0.1278108	-0.7087668	3.2145007	0.1607094
0.6	0.1858261	-0.6701024	2.8108362	0.1424566
0.7	0.2701053	-0.6340573	2.6013829	0.1253063
0.8	0.3925044	-0.6075992	2.5809287	0.1092863

beta	alpha	rho	nu	objective
0.9	0.5711641	-0.5787124	2.5210188	0.0945451
1.0	0.8313951	-0.8933951	0.0301414	0.0816091

```
opts.long <- melt(opts, id="beta")
ggplot(data=opts.long, aes(x=beta, y=value, color=variable)) + geom_line()
```



To be more precisely, in this section, let beta equal to 0, 0.1, 0.2, ... 1. Still, objective value is decreasing as beta growing. We can basically say that beta=1 gives me the best estimation.

5

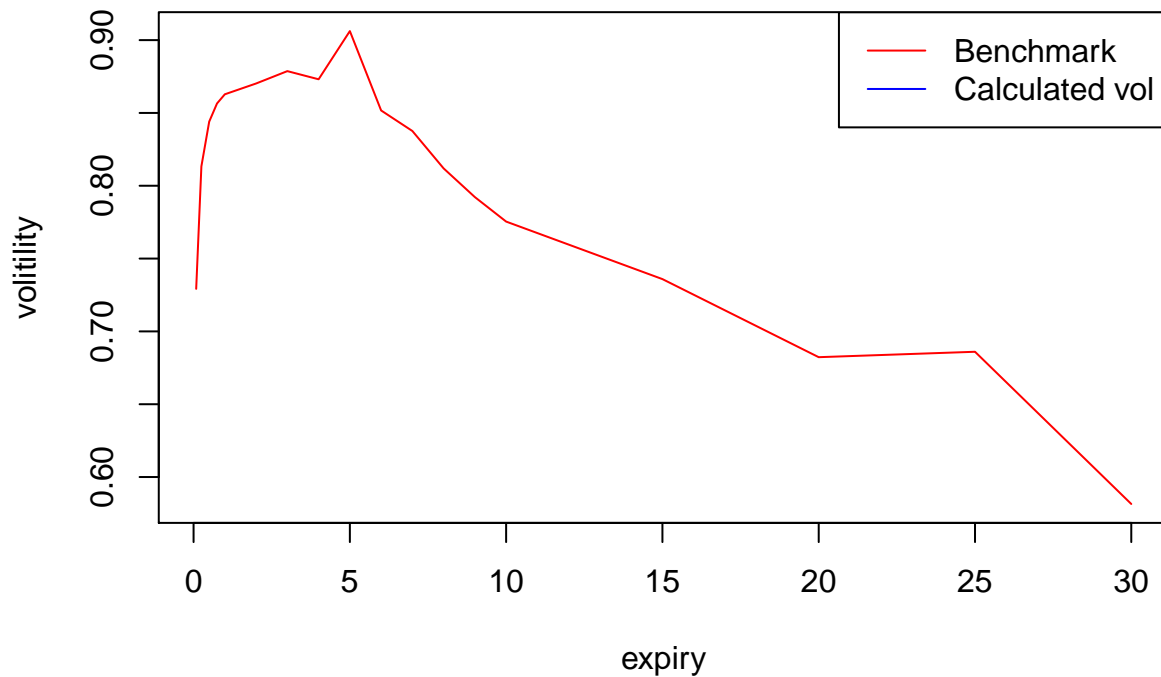
```
beta <- 1
re5 <- optimization(beta)
alpha <- re3[2]
rho <- re3[3]
nu <- re3[4]

column <- 7 # choose 7th maturity which is 10 years
Vol2 <- swaptions[seq(1, 38, by=2), 9]/100 # At-the-money volatility
Strike2 <- swaptions[seq(2, 38, by=2), 9]/100 # Strike price K

VolB <- SABRVol(alpha,beta,rho,nu,expiry,Strike2)
plot(expiry, Vol2, type = "l", col = "red", ylab = "volatility")
lines(expiry, VolB, col = "blue")
```



```
legend("topright", legend=c("Benchmark", "Calculated vol"),
      col=c("red", "blue"), lty=c(1,1))
```



```
obj <- sum((VolB-Vol2)^2)
obj
```

```
## [1] 7.495555
```

Apply $\beta = 1$ to swaps whose maturity is 10 years. The volatility calculated by SABR model is nearly a straight line. Given volatilities fluctuate around it. The SSE is 0.05352116 which is fairly small.

3

```
S0=1
Tm=1
sigma=0.2
r=0.0075

alpha <- 1
N <- 10000
eta <- 50
lambda <- 2*pi/N/eta
a <- N*eta # the effective upper limit for the integration
b <- N*lambda/2 # log of strike prices range from -b to b

# for phi_T
f_phi<- function(u, s, mu, sigma) {
  # integrand
  ans <- 1/sqrt(2*pi*sigma^2)*exp(-(s-mu)^2/2/sigma^2)*exp(1i*u*s)
  return(ans)
}
```

```

phi_u <- function(u, mu, sigma, a, N) {
  # Integral
  # By the Simpson's rule
  s <- seq(-a, a, length.out = N)
  h <- s[2] - s[1]
  wn <- rep(c(2*h/3, 4*h/3), floor(N/2))
  wn[1] <- h/3
  wn[N] <- h/3
  fn <- sapply(s, f_phi, u = u, mu = mu, sigma = sigma)
  ans <- sum(fn*wn)
  return(ans)
}

# Out the money
zeta_v <- function(v, r, Tm, mu, sigma, a, N) {
  ans <- exp(-r*Tm)*(1/(1 + 1i*v) - exp(r*Tm)/(1i*v) -
    phi_u(v - 1i, mu, sigma, a, N)/(v^2 - 1i*v))
  return(ans)
}

gamma_v <- function(v, r, Tm, mu, sigma, alpha, a, N) {
  ans <- (zeta_v(v - 1i*alpha, r, Tm, mu, sigma, a, N) -
    zeta_v(v + 1i*alpha, r, Tm, mu, sigma, a, N))/2
  return(ans)
}

# In the money
psi_v <- function(v, r, Tm, mu, sigma, alpha, a, N) {
  ans <- (exp(-r*Tm)*phi_u(v - (alpha + 1)*1i, mu, sigma, a, N))/
    (alpha^2 + alpha - v^2 + 1i*(2*alpha + 1)*v)
  return(ans)
}

Call_FFT <- function(u, r, Tm, mu, sigma, alpha, a, N) {
  ku <- -b + lambda*(u-1)
  s <- seq(0.0001, a, length.out = N)
  h <- s[2] - s[1]
  wn <- rep(c(2*h/3, 4*h/3), floor(N/2))
  wn[1] <- h/3
  wn[N] <- h/3
  j <- seq(1, N)
  vj <- (j-1)*eta
  if (u < ((N+1)/2)) {
    f <- exp(-1i*2*pi/N*(j-1)*(u-1))*exp(1i*b*vj)*psi_v(vj, r, Tm, r, sigma, alpha, a, N)
    C <- exp(-alpha*k)/pi*sum(f*wn)
  } else {
    f <- exp(-1i*2*pi/N*(j-1)*(u-1))*exp(1i*b*vj)*gamma_v(vj, r, Tm, r, sigma, alpha, a, N)
    C <- sinh(alpha*k)/pi*sum(f*wn)
  }
  return(C)
}
u=60

```

```

Call_FFT(u, r, Tm, r, sigma, alpha, a, N)

## [1] NaN+NaNi

K <- (-b + (u-1)*lambda)^2
Option_BSM <- function(isCall = T, S0=1, K=1, Tm=1, sigma=0.2, r=0.0075, div=0) {
  d1 <- (log(S0/K) + (r - div + sigma^2/2)*Tm)/sigma/sqrt(Tm)
  d2 <- d1 - sigma*sqrt(Tm)
  if (isCall) {p <- S0*exp(-div*Tm)*pnorm(d1) - K*exp(-r*Tm)*pnorm(d2)}
  else {p <- K*exp(-r*Tm)*pnorm(-d2) - S0*exp(-div*Tm)*pnorm(-d1)}
  return(p)
}
Option_BSM(K=K)

## [1] 0.9961736

```