R Textbook Companion for Numerical Methods in Finance and Economics: A MATLAB-Based Introduction by Paolo Brandimarte¹

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Book Description

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Introduction

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R numbering policy used in this document and the relation to the above book.

Exa Example (Solved example)

Eqn Equation (Particular equation of the above book)

For example, Exa 3.51 means solved example 3.51 of this book. Sec 2.3 means an R code whose theory is explained in Section 2.3 of the book.

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Chapter 2

Financial Theory

R code Exa 2.7 Basic theory of interest rates

```
1 mypvvar <- function(cf,r) {</pre>
     # get number of periods
    n = length(cf)
   #1 get vector of discount factors
     df <-matrix(0,n)</pre>
     for (i in 0:n-1){
        df[i+1] = 1/(1+r)^(i)
8
     #compute result
10
     pv = cf*df
11 }
12
13 \text{ cf} \leftarrow c(0, 8, 8, 8, 8, 108)
14 \text{ pv} = \text{mypvvar} (cf, 0.08)
15 sum(pv)
16
17 \text{ pv} = \text{mypvvar} (cf, 0.09)
18 sum(pv)
19
20 \text{ pv} = \text{mypvvar} (cf, 0.07)
21 sum(pv)
```

R code Exa 2.8 Basic theory of interest rates

```
1 #install.packages("FinCal")
2 library("FinCal")
3 cf<-c(-100, 8, 8, 8, 8, 108)
4 h=polyroot(cf[length(cf):1])
5 h
6 rho=1/h-1
7 rho
8 index = which((abs(Im(rho)) < 0.001) != 0)
9 rho[index]
10 irr(cf)</pre>
```

R code Exa 2.9 Basic pricing of fixed income securities

```
1 mypvvar <- function(cf,r) {</pre>
2
     # get number of periods
     n = length(cf)
3
4
     #1 get vector of discount factors
     df <-matrix(0,n)</pre>
6
     for (i in 0:n-1){
       df[i+1] = 1/(1+r)^(i)
     }
8
9
     #compute result
     pv = cf*df
10
11 }
12
13 r1=0.08
14 r2=0.09
15 P1=100/(1+r1)^5
16 P1
```

```
17 P2=100/(1+r2)^5
18 P2
19 (P2-P1)/P1
20
21 P1=100/(1+r1)^20
22 P1
23 P2=100/(1+r2)^20
24 P2
25 (P2-P1)/P1
26
27 cf1<-c(0, 8, 8, 8, 8, 8, 8, 8, 8, 8, 108)
28 \text{ cf2} < -c(0, 4, 4, 4, 4, 4, 4, 4, 4, 4, 104)
29 P1=mypvvar(cf1,0.08)
30 \text{ P1} = \text{sum}(\text{P1})
31 P1
32 P2=mypvvar(cf1,0.09)
33 P2 = sum(P2)
34 P2
35 (P2-P1)/P1
36 P1=mypvvar(cf2,0.08)
37 P1 = sum(P1)
38 P1
39 P2=mypvvar(cf2,0.09)
40 P2 = sum(P2)
41 P2
42 (P2-P1)/P1
```

R code Exa 2.10 Interest rate sensitivity and bond portfolio immunization

```
1 library(FinCal)
2 mypvvar <- function(cf,r) {
3  # get number of periods
4  n = length(cf)
5  #1 get vector of discount factors
6 df<-matrix(0,n)</pre>
```

```
for (i in 0:n-1){
7
8
       df[i+1] = 1/(1+r)^(i)
9
10
     #compute result
11
     pv = cf*df
12 }
13
14 cfdur <- function(cf,yld) {</pre>
15
         CFDUR Cash flow duration and modified
        duration.
         [D,MD] = CFDUR(CF,YLD) calculates the duration
16
         D and modified duration
17
         (volatility) MD of a cash flow given the cash
        flow, CF, and the periodic
         yield, YLD.
18
19
     #
20
         For example, nine payments of $2.50 and a
        final payment of $102.50 with
         a yield of 2.5% returns a duration of 8.97
21
        periods and a modified duration
22
         of 8.75 periods.
23
         See also BONDCONV, BONDDUR, CFCONV.
24
25
         Copyright 1995-2006 The MathWorks, Inc.
26
     x < -dim(cf)
     rowcf = x[1]
27
28
     colcf = x[2]
29
     if (rowcf == 1){
30
       cf = t(cf)
31
       colcf = 1
32
     }
33
34
     if (colcf > 1 ){
       if (length(yld) == 1){
35
         yld = yld*matrix(1,colcf)
36
37
       }
38
     }
39
```

```
40
     pv = matrix(0,colcf)
     d = pv
41
     md = pv
42
     m = length(cf[,1])
43
44
     fac = t((1:m))
45
     for (loop in 1:colcf){
       # Compound the yield
46
       rates = (matrix(data = 1, ncol = m, nrow = 1)*(1+
47
          vld[loop]))^fac
       # find the net present value
48
       pv[loop] = sum(mypvvar(c(0,cf[,loop]),yld[loop])
49
       # duration
50
       d[loop] = sum(cf[,loop]/(rates)*fac)/pv[loop]
51
       # modified duration
52
53
       md[loop] = d[loop]/(1+yld[loop])
54
55
     cat("Duration of cash flow:",d,"\n")
     cat ("Modified Duration (volatility) of cash flow:"
56
        , md , "\n")
     return(list(d=d,dm=md))
57
58 }
59
60 cfconv <- function(cf,yld) {
         CFCONV Cash flow convexity.
61
         CX = CFCONV(CF, YLD) calculates the convexity C
62
         of a cash flow
         given the cash flow, CF, and the periodic
63
        yield, YLD.
64
65
         For example, nine payments of $2.50 and a
        final payment of $102.50
66
         with a yield of 2.5% returns a convexity of
        90.45 periods.
67
         See also BONDCONV, BONDDUR, CFDUR.
68
     #
69
70
             Copyright 1995-2006 The MathWorks, Inc.
     #
```

```
71
      x < -dim(cf)
72
      rowcf = x[1]
73
       colcf = x[2]
      if (rowcf == 1){
74
75
         cf = t(cf)
 76
         colcf = 1
77
      }
78
79
      if (colcf > 1 ){
         if (length(yld) == 1){
80
           yld = yld*matrix(1,colcf)
81
82
         }
83
      }
84
85
      pv = matrix(0,colcf)
86
      cx = pv
87
      m = length(cf[,1])
88
       fac = t((1:m))
       for (loop in 1:colcf){
89
         #Compound the yield
90
91
         rates = (matrix(data = 1, ncol = m, nrow = 1)*(1+
            yld[loop]))^fac
         #find the net present value
92
         pv[loop] = sum(mypvvar(c(0,cf[,loop]),yld[loop])
93
         cx[loop] = sum(cf[,loop]/(rates)*fac*(fac+1))/
94
            ((1+yld[loop])^2*pv[loop])
95
96
       cat("Cash flow convexity:",cx,"\n")
       return(cx)
97
98 }
99
100 \text{ cf} < -c (10, 10, 10, 10)
101 p1=abs(pv.uneven(0.05,cf))
102 p2=abs(pv.uneven(0.055,cf))
103 (p2-p1)
104 \text{ cf} < -\text{matrix}(\text{cf}, \text{nrow} = 1, \text{ncol} = 4)
105 \text{ yld} \leftarrow \text{matrix}(\text{data} = \text{c}(0.05), \text{nrow} = 1, \text{ncol} = 1)
```

```
106 x <-cfdur(cf,yld)

107 d <-x$d

108 dm <-x$dm

109 cv = cfconv(cf,yld)

110 -dm * p1 * 0.005

111 -dm * p1 * 0.005 + 0.5 * cv * p1 * (0.005) ^2
```

R code Exa 2.24 Black Scholes model in MATLAB

Chapter 3

Basics of Numerical Analysis

R code Exa 3.2 Error propagation conditioning and instability

R code Exa 3.4 Vector and matrix norms

R code Exa 3.6 Vector and matrix norms

R code Exa 3.7 Condition number for a matrix

```
1 #install.packages("Matrix")
2 require(Matrix)
3 kappa(Hilbert(3), exact = TRUE)
4 kappa(Hilbert(7), exact = TRUE)
5 kappa(Hilbert(10), exact = TRUE)
```

R code Exa 3.8 Condition number for a matrix

```
1 N = 20
2 A < -diag(N)
3
4 for (i in 1:N) {
5    for (j in (i+1):N) {
6        A[i,j] = -1
7    }
8 }
9
10 b=-rep(1,N)</pre>
```

```
11 b[N] = 1

12 solve(A,b)

13

14 b[N] = 1.00001

15 solve(A,b)

16

17 1/rcond(A,'I')

18 2^18

19 0.00001 * 2^18
```

R code Exa 3.11 Direct methods for solving systems of linear equations

R code Exa 3.12 Direct methods for solving systems of linear equations

R code Exa 3.13 Iterative methods for solving systems of linear equations

```
Jacobi <- function(A,b,x0,eps,MaxIter) {</pre>
     dA = diag(A)
3
     C = A - diag(dA)
     Dinv = diag(1/dA)
4
     B = - Dinv %*% C
     b1 = Dinv \%*\% b
6
7
     oldx = x0
8
9
     for (i in 1:MaxIter){
10
        x = B \% *\%  oldx + b1
11
        if (norm(x-oldx) < eps*norm(matrix(oldx))){</pre>
12
          break
        }
13
14
        oldx = x
15
     cat ("Case of Matrix:", A, "\n")
16
17
     cat ("Terminated after iterations:",i,"\n")
     cat("Jacobi:",x,"\n")
18
     cat("Exact:",solve(A,b),"\n")
19
20 }
21
22 A1 <-matrix(c(3, 1, 1, 0, 1, 5, -1, 2, 1, 0, 3, 1,
      0, 1, 1, 4), nrow = 4, ncol = 4, byrow = T
23 b \leftarrow matrix(c(1, 4, -2, 1), mrow = 4, mcol = 1, byrow = T
  Jacobi (A1,b,rep(0,4),1e-08,10000)
24
25
26 \text{ A2} \leftarrow \text{matrix}(c(2.5, 1, 1, 0, 1, 4.1, -1, 2, 1, 0,
      2.1, 1, 0, 1, 1, 2.1), nrow = 4, ncol = 4, byrow = T
27 Jacobi (A2, b, rep (0,4), 1e-08, 10000)
```

```
28

29 A3 <-matrix(c(2, 1, 1, 0, 1, 3.5, -1, 2, 1, 0, 2.1, 1, 0, 1, 1, 2.1), nrow = 4, ncol = 4, byrow = T)

30 Jacobi(A3,b,rep(0,4),1e-08,10000)
```

R code Exa 3.14 Iterative methods for solving systems of linear equations

```
1 SORGaussSeidel <- function(A, b,x0, omega, eps,</pre>
      MaxIter) {
2
     oldx = x0
     x = x0
3
     N = length(x0)
     omega1 = 1 - omega
6
     for (k in 1:MaxIter){
       for (i in 1:(N-1)){
8
          z = (b[i] - sum(A[i,(1:i-1)]) * x[1:(i-1)]) -
             sum(A[i,(i+1):N] * x[(i+1):N]) / A[i,i]
9
          x[i] = omega * z + omega1 * oldx[i]
       }
10
        if (norm(matrix(x-oldx)) < eps*norm(matrix(oldx))) {</pre>
11
12
          break
       }
13
14
       oldx = x
15
     }
16
     result$x = x
     result$k = k
17
     return(result)
18
19 }
20
21 A2<-matrix(c(2.5, 1, 1, 0, 1, 4.1, -1, 2, 1, 0, 2.1,
       1, 0, 1, 1, 2.1), nrow = 4, ncol = 4, by row = T)
22 b \leftarrow matrix(c(1, 4, -2, 1), nrow = 4, ncol = 1, byrow = T
      )
23 \text{ omega} = \text{seq}(0,2,0.1)
24 N = length (omega)
```

 ${f R}$ code Exa 3.15 FUNCTION APPROXIMATION AND INTERPOLATION

```
1 xdata < -c(1, 5, 10, 30, 50)
2 ydata <-log(xdata)</pre>
3 p = coef(lm(ydata ~ xdata + I(xdata^2)))
4 p
6 \times = c(1, 5, 10, 30, 50)
7 y = log(x)
8 \text{ plot}(x,y)
9 \quad lm2 = lm(y~x+I(x~2))
10 lm4 = lm(y^x+I(x^2)+I(x^3)+I(x^4))
11 xplot=seq(from = 0, to = 50, by = .1)
12 lines(xplot, predict(lm4, newdata=data.frame(x=xplot))
      , col="blue")
13 \# and so on
14 lines(xplot, predict(lm2, newdata=data.frame(x=xplot))
      , col="red")
15
16 #http://www.utstat.utoronto.ca/reid/sta414/Rsession-
      polys.pdf
```

R code Exa 3.16 Elementary polynomial interpolation

```
1 x=1:10
2 y<-c(8, 2.5, -2, 0 ,5 ,2 ,4 ,7 ,4.5, 2)
3 lm9 = lm(y~x+I(x^2)+I(x^3)+I(x^4)+I(x^5)+I(x^6)+I(x ^7)+I(x^8)+I(x^9))
4 xplot=seq(from = 0,to = 10,by = .05)
5 plot(x,y)
6 lines(xplot,predict(lm9,newdata=data.frame(x=xplot)), col="blue")</pre>
```

R code Exa 3.17 Elementary polynomial interpolation

```
1 runge <- function(x) {</pre>
     1/(1+25*x^2)
2
3 }
4
5 \text{ EquiNodes} = -5:5
6 peq = coef(lm(runge(EquiNodes)~EquiNodes+I(EquiNodes
      ^2) + I (EquiNodes ^3) + I (EquiNodes ^4) + I (EquiNodes ^5) +
      I(EquiNodes^6)+I(EquiNodes^7)+I(EquiNodes^8)+I(
      EquiNodes ^9) +I (EquiNodes ^10)))
7
8 x = -5:5
9 y = runge(x)
10 \quad 1m10 = \frac{1m}{y^{x}+I(x^{2})+I(x^{3})+I(x^{4})+I(x^{5})+I(x^{6})+I(x^{6})}
      ^{7}) + I(x^{8}) + I(x^{9}) + I(x^{10})
11 xplot=seq(from = -5, to = 5, by = .01)
12 \text{ plot}(x,y,asp = .33)
13 lines(x,y)
14 grid(10,10)
15 lines(xplot, predict(lm10, newdata=data.frame(x=xplot)
      ), col="blue")
16
17 ChebNodes = 5*cos(pi*(11 - (1:11) + 0.5)/11)
```

R code Exa 3.18 Interpolation by cubic splines

```
1 require(pracma)
 3 x=1: 10
 4 \text{ y} < -c(8, 2.5, -2, 0, 5, 2, 4, 7, 4.5, 2)
 5 plot(x,y)
 6 	ext{ x2} < -\text{seq} (\text{from} = 1, \text{ to} = 10, \text{ by} = 0.05)
 7 y2=interp1(x,y,x2, 'spline')
8 lines(x2,y2)
10 x = 1: 10
11 y \leftarrow c(8, 2.5, -2, 0, 5, 2, 4, 7, 4.5, 2)
12 plot(x,y)
13 pp=cubicspline (x, y)
14 \text{ x2} < -\text{seq} (\text{from} = 1, \text{to} = 10, \text{by} = 0.05)
15 \text{ y2} = \text{ppval}(\text{pp}, \text{x2})
16 lines(x2,y2)
17
18 runge <- function(x) {</pre>
```

```
19
     1/(1+25*x^2)
20 }
21
22 # use 11 equispaced nodes
23 EquiNodes11 = -5:5
24 ppeq11 = cubicspline(EquiNodes11, runge(EquiNodes11))
25 \text{ xplot} = \text{seq}(\text{from} = -5, \text{ to} = 5, \text{ by} = 0.01)
26
27 # use 20 equispaced nodes
28 EquiNodes20 = linspace(-5,5,20)
29 ppeq20 = cubicspline(EquiNodes20, runge(EquiNodes20))
30 \text{ xplot} = \text{seq}(\text{from} = -5, \text{ to} = 5, \text{ by} = 0.01)
31
32 # use 21 equispaced nodes
33 EquiNodes21 = linspace (-5,5,21)
34 ppeq21 = cubicspline(EquiNodes21, runge(EquiNodes21))
35 \text{ xplot} = \text{seq}(\text{from} = -5, \text{ to} = 5, \text{by} = 0.01)
36
37 \text{ par}(\text{mfrow}=c(3,1))
38 plot(EquiNodes11, runge(EquiNodes11), asp = 1)
39 lines (EquiNodes11, runge (EquiNodes11))
40 lines(xplot,ppval(ppeq11,xplot), col="blue")
41 plot(EquiNodes20, runge(EquiNodes20), asp = 1)
42 lines (EquiNodes20, runge (EquiNodes20))
43 lines(xplot,ppval(ppeq20,xplot), col="blue")
44 plot(EquiNodes21, runge(EquiNodes21), asp = 1)
45 lines(EquiNodes21, runge(EquiNodes21))
46 lines(xplot,ppval(ppeq21,xplot), col="blue")
```

R code Exa 3.22 Bisection method

```
1 f <- function(x) {
2   1/x
3 }
4 ans = uniroot(f,c(-1,1),tol=2^-52)</pre>
```

```
5 ans$root
6 ans$f.root
7
8 #z<-curve(f)
9
10 f <- function(x) {
11    x^2
12 }
13 ans2 = uniroot(f,c(-1,1),tol=2^-52)
14 ans2$root
15 ans2$f.root</pre>
```

R code Exa 3.23 Newtons method

```
1 require(OptionPricing)
2 c=BS_EC(K=54, r = 0.07, sigma = 0.3, T = 5/12, S0 = 50)
3 c[1]
4 y <- function(y) (BS_EC(K=54, r = 0.07, sigma = y, T = 5/12, S0 = 50)[1]-2.846575)
5 h<-Vectorize(y)
6 uniroot(y,c(-1,1))
7
8 f <- Vectorize(function(y) (BS_EC(K=54, r = 0.07, sigma = y, T = 5/12, S0 = 50)[1]-2.846575))
9 curve(f)</pre>
```

R code Exa 3.24 Optimization based solution of non linear equations

```
1 require(pracma)
2 f <- function(x) x^3*exp(-x^2)
3 vx<-seq(-4,4,.05)
4 plot(vx,f(vx))</pre>
```

```
5 lines(vx,f(vx))
6 fsolve(f,1)
7 fsolve(f,2)
8
9 #fsolve answers defer from matlab (book)
```

Chapter 4

Numerical Integration Deterministic and Monte Carlo Methods

R code Exa 4.1 Numerical integration in MATLAB

```
1 #require(pracma)
2 f <- function(x) {
3   exp(-x)*sin(10*x)
4 }
5
6 integrate(f ,0,2*pi)
7
8 integrate(f ,0,2*pi,abs.tol = 10e-6)
9
10 integrate(f ,0,2*pi,abs.tol = 10e-8)
11
12 quadl(f ,0,2*pi)</pre>
```

R code Exa 4.2 MONTE CARLO INTEGRATION

```
1  set.seed(12345)
2  mean(exp(runif(10)))
3  mean(exp(runif(10)))
4  mean(exp(runif(10)))
5  mean(exp(runif(1000000)))
6  mean(exp(runif(1000000)))
7  mean(exp(runif(1000000)))
```

R code Exa 4.3 MONTE CARLO INTEGRATION

```
1 BlsMC1 <- function(S0, K , r , T , sigma, NRepl) {</pre>
     nuT = (r - 0.5*sigma**2)*T
3
     siT = sigma * sqrt(T)
     DiscPayoff = exp(-r*T) *pmax(0,(S0*exp(nuT+siT*
        rnorm(NRepl))-K))
     Price = mean(DiscPayoff)
5
     return(Price)
6
7 }
8 S0 = 50
9 K = 60
10 r = 0.05
11 T=1
12 \text{ sigma=0.2}
13 set.seed (547)
14 BlsMC1(S0,K,r ,T, sigma, 1000)
15 BlsMC1(SO,K,r,T, sigma, 1000)
16 BlsMC1(S0,K,r ,T, sigma, 1000)
17 BlsMC1(S0,K,r,T, sigma, 1000000)
18 BlsMC1(SO,K,r,T, sigma, 1000000)
19 BlsMC1(SO,K,r,T, sigma, 1000000)
```

R code Exa 4.4 Generating pseudorandom numbers

```
1 LCG <- function(a,c,m,seed,N) {</pre>
2
      ZSeq <-matrix(0,N,1)</pre>
     USeq <-matrix(0,N,1)</pre>
3
4
     for (i in 1:N){
        seed = (a*seed+c) \% m
5
6
        ZSeq[i] = seed
7
        USeq[i] = seed/m
8
9
     result <-list(ZSeq, USeq)</pre>
      return(result)
10
11 }
12
13 \ a = 5
14 c = 3
15 \, \text{m} = 16
16 \text{ seed} = 7
17 N = 20
18 LCG(a,c,m,seed,N)
```

R code Exa 4.5 Generating pseudorandom numbers

```
1 LCG <- function(a,c,m,seed,N) {</pre>
2
      ZSeq <-matrix(0,N,1)</pre>
3
     USeq <-matrix(0,N,1)</pre>
4
     for (i in 1:N){
        seed = (a*seed+c) %% m
5
6
        ZSeq[i] = seed
7
        USeq[i] = seed/m
8
     }
9
     result <-list(ZSeq, USeq)</pre>
      return(result)
10
11 }
12
13 m = 2048;
14 \ a = 65;
```

```
15  c = 1;
16  seed = 0;
17  U = LCG(a,c,m,seed, 2048);
18  plot(unlist(U[1])[1:m-1],unlist(U[2])[2:m])
19  plot(unlist(U[1])[1:511],unlist(U[2])[2:512])
20
21  a=1365;
22  c=1 ;
23  U = LCG(a,c,m,seed, 2048)
24  plot(unlist(U[1])[1:m-1],unlist(U[2])[2:m])
```

R code Exa 4.6 Inverse transform method

```
1 set.seed(64657)
2 \text{ rexp}(1, 1/1)
4 EmpiricalDrnd <- function(values, probs, howmany) {
     cumprobs = cumsum(probs)
     N = length(probs)
7
     samples = matrix(0,howmany, 1)
     for (k in 1:howmany){
       loc=sum(runif(1)*cumprobs[N] > cumprobs) + 1;
9
       samples[k] = values[loc]
10
11
12
     return(samples)
13 }
14
15 values=1:5
16 probs <-c (0.1, 0.2, 0.4, 0.2, 0.1)
17 samples=EmpiricalDrnd(values ,probs ,10000)
18 \text{ hist}(x = samples)
```

R code Exa 4.8 Generating normal variates by the polar approach

```
1 LCG <- function(a,c,m,seed,N) {</pre>
2
      ZSeq <-matrix(0,N,1)</pre>
3
      USeq \leftarrowmatrix(0,N,1)
      for (i in 1:N){
4
5
        seed = (a*seed+c) %% m
6
        ZSeq[i] = seed
7
        USeq[i] = seed/m
8
9
      result <-list (ZSeq, USeq)
      return(result)
10
11 }
12
13 m = 2048;
14 \ a = 1229;
15 c = 1;
16 N = m-2;
17 \text{ seed} = 0;
18 U = LCG(a, c, m, seed, N);
19 index < -seq(1, N-1, 2)
20 \text{ U1} = \text{unlist}(\text{U}[2])[\text{index}]
21 \quad index < -seq(2,N,2)
22 U2 = unlist(U[2])[index]
23 X = sqrt(-2*log(U1))*cos(2*pi*U2);
24 \ Y = sqrt(-2*log(U1))* sin(2*pi*U2);
25 plot(X,Y)
26 \text{ X=} \text{sqrt}(-2*\log(U2))* \cos(2*pi*U1);
27 \text{ Y=sqrt}(-2*log(U2))*sin(2*pi*U1);
28 plot(X,Y)
```

R code Exa 4.9 Generating normal variates by the polar approach

```
4 set.seed(2392)
6 MultiNormrnd <- function(mu, sigma, howmany) {
     n = length(mu)
7
     Z = matrix(0, howmany, n)
9
     U = chol(sigma)
10
     for (i in 1:howmany){
       Z[i,] = t(mu) + t(matrix(rnorm(n))) %*% U
11
12
     }
    return(Z)
13
14 }
15
16 Z = MultiNormrnd(mu, Sigma, 10000)
17 mean(Z[1])
18 mean(Z[2])
19 mean(Z[3])
20 \operatorname{cov}(Z)
```

R code Exa 4.10 SETTING THE NUMBER OF REPLICATIONS

```
1 #require (fBasics)
2 norm.interval = function(data, variance = var(data),
      conf.level = 0.95) {
        z = qnorm((1 - conf.level)/2, lower.tail =
3
           FALSE)
        xbar = mean(data)
4
        sdx = sqrt(variance/length(data))
6
        c(xbar - z * sdx, xbar + z * sdx)
7
        }
9 BlsMC2 <- function(SO,K,r,T,sigma,NRepl) {
    nuT = (r - 0.5*sigma^2)*T;
10
     siT = sigma * sqrt(T);
11
12
     DiscPayoff = exp(-r*T)*pmax(0, S0*exp(nuT+siT*
       rnorm(NRepl))-K);
```

```
13
      parameter_estimation <-. normFit (DiscPayoff)</pre>
      ci<-norm.interval(DiscPayoff)</pre>
14
      final <-list (parameter_estimation, ci)</pre>
15
      return(final)
16
17 }
18
19 set.seed (483762)
20 \text{ SO} = 50;
21 \text{ K=55};
22 r = 0.05;
23 T=5/12;
24 \text{ sigma=0.2};
25 answer <-BlsMC2(S0,K,r,T,sigma,50000)
26 \text{ answer2} \leftarrow BlsMC2(S0,K,r,T,sigma,1000000)
27 \# (answer[[2]][2] - answer[[2]][1]) / 1.168224
28 #(answer2[[2]][2] - answer2[[2]][1])/1.173184
```

R code Exa 4.11 Antithetic sampling

```
1 #require (fBasics)
2 norm.interval = function(data, variance = var(data),
       conf.level = 0.95) {
     z = qnorm((1 - conf.level)/2, lower.tail = FALSE)
3
     xbar = mean(data)
     sdx = sqrt(variance/length(data))
     c(xbar - z * sdx, xbar + z * sdx)
7 }
8 set.seed(337282)
9 X = exp(runif(100))
10 parameter_estimation<-.normFit(X)</pre>
11 ci<-norm.interval(X)</pre>
12 #from parameter estimation, value of mean =
      1.7031094
13 (ci[2]-ci[1])/1.7031094
14
```

R code Exa 4.12 BlsMCAV

```
1 suppressMessages(require(fBasics))
2 norm.interval = function(data, variance = var(data),
       conf.level = 0.95) {
     z = qnorm((1 - conf.level)/2, lower.tail = FALSE)
3
     xbar = mean(data)
     sdx = sqrt(variance/length(data))
     c(xbar - z * sdx, xbar + z * sdx)
7 }
9 BlsMCAV <- function(SO,K,r,T,sigma,NPairs) {
     nuT = (r - 0.5*sigma^2)*T;
10
11
     siT = sigma * sqrt(T);
12
     Veps = rnorm(NPairs);
     Payoff1 = pmax(0, S0*exp(nuT+siT*Veps) - K);
13
     Payoff2 = pmax(0, S0*exp(nuT+siT*(-Veps)) - K);
14
15
     DiscPayoff = \exp(-r*T) * 0.5 * (Payoff1+Payoff2);
     parameter_estimation <-.normFit(DiscPayoff)</pre>
16
     ci<-norm.interval(DiscPayoff)</pre>
17
18
     answer <-list(parameter_estimation,ci)</pre>
19
     return(answer)
20 }
21
22 BlsMC2 <- function(SO,K,r,T,sigma,NRepl) {
```

```
23
     nuT = (r - 0.5*sigma^2)*T;
24
     siT = sigma * sqrt(T);
     DiscPayoff = exp(-r*T)*pmax(0, S0*exp(nuT+siT*
25
        rnorm(NRepl))-K);
26
     parameter_estimation <-.normFit(DiscPayoff)</pre>
27
     ci<-norm.interval(DiscPayoff)</pre>
     final <-list(parameter_estimation,ci)</pre>
28
     return(final)
29
30 }
31
32 MCButterfly <- function(SO,r,T,sigma,NRepl,K1,K2,K3)
33
     nuT = (r-0.5*sigma^2)*T;
34
     siT = sigma*sqrt(T);
     Veps = rnorm(NRepl);
35
     Stocks = S0*exp(nuT + siT*Veps);
36
     In1 = which((Stocks > K1) & (Stocks < K2));</pre>
37
     In2 = which((Stocks >= K2) & (Stocks < K3));</pre>
38
     Payoff = \exp(-r*T)*matrix(c((Stocks[In1]-K1)),
39
        -Stocks[In2]), matrix(0,(NRepl - length(In1) -
        length(In2)),1)))
     parameter_estimation <-. normFit (Payoff)</pre>
40
     ci<-norm.interval(Payoff)</pre>
41
     final <-list(parameter_estimation,ci)</pre>
42
     return(final)
43
44 }
45
46 MCAVButterfly <- function(SO,r,T,sigma,NPairs,K1,K2,
      K3) {
     nuT = (r-0.5*sigma^2)*T;
47
     siT = sigma*sqrt(T);
48
49
     Veps = rnorm(NPairs);
     Stocks1 = S0*exp(nuT + siT*Veps);
50
     Stocks2 = S0*exp(nuT - siT*Veps);
51
     Payoff1 = matrix(0, NPairs,1);
52
     Payoff2 = matrix(0, NPairs, 1);
53
     In = which((Stocks1 > K1) & (Stocks1 < K2));</pre>
54
     Payoff1[In] = (Stocks1[In] - K1);
55
```

```
In = which((Stocks1 >= K2) & (Stocks1 < K3));
56
57
     Payoff1[In] = (K3 - Stocks1[In]);
     In = which((Stocks2 > K1) & (Stocks2 < K2));</pre>
58
     Payoff2[In] = (Stocks2[In] - K1);
59
60
     In = which((Stocks2 >= K2) & (Stocks2 < K3));
61
     Payoff2[In] = (K3 - Stocks2[In]);
62
     Payoff = 0.5 * exp(-r*T) * (Payoff1 + Payoff2);
     parameter_estimation <-.normFit(Payoff)</pre>
63
     ci<-norm.interval(Payoff)</pre>
64
     final <-list (parameter_estimation, ci)</pre>
65
     return(final)
66
67 }
68
69 set.seed(3374)
70 \text{ Y} \leftarrow \text{BlsMC2}(50,50,0.05,1,0.4,200000)
71 #from parameter estimation, value of mean = 9.11143
72 (Y[[2]][2]-Y[[2]][1])/9.11143
73
74 Z<-BlsMCAV(50,50,0.05,1,0.4,100000)
75 #from parameter estimation, value of mean = 9.020972
76 \quad (Z[[2]][2]-Z[[2]][1])/9.020972
77
78 set.seed(39489378)
79 \text{ SO} = 60;
80 \text{ K1} = 55;
81 \text{ K2} = 60;
82 \text{ K3} = 65;
83 T = 5/12;
84 r = 0.1;
85 \text{ sigma} = 0.4;
86 a <-MCButterfly(SO,r,T,sigma,100000,K1,K2,K3);
87 #from parameter estimation, value of mean =
      0.6104167
88 (a[[2]][2]-a[[2]][1])/0.6104167
89
90 set.seed(72725)
91 b <-MCAVButterfly(SO,r ,T, sigma,50000,K1 ,K2,K3)
92 #from parameter estimation, value of mean =
```

R code Exa 4.14 Importance sampling

```
1 estpi <- function(m) {</pre>
2
     z=sqrt(1-runif(m)^2);
3
     out = 4*sum(z)/m;
     return(out)
4
5 }
6 set.seed (483272)
7 estpi(1000)
8 estpi(1000)
9 estpi(1000)
10
11 estpiIS <- function(m,L) {</pre>
12
     s = seq(0,1-1/L,1/L) + 1/(2*L)
     hvals = matrix(sqrt(1 - s^2))
13
     # get cumulative probabilities
14
15
     cs=apply(hvals,2,cumsum);
16
     est = matrix(0,m)
     for (j in 1:m){
17
       # locate sub-interval
18
       loc=sum(runif(1)*cs[L] > cs) +1;
19
       # sample uniformly within sub-interval
20
       x=(loc-1)/L + runif(1)/L;
21
22
       p=hvals[loc]/cs[L];
       est[j] = sqrt(1 - x^2)/(p*L);
23
24
     }
25
     plot(est)
     z = 4*sum(est)/m;
26
27
     return(z)
28 }
29
30 estpiIS(1000,10)
```

```
31 estpiIS(1000,10)

32 estpiIS(1000,10)

33 estpiIS(1000,100)

34 estpiIS(1000,100)

35 estpiIS(1000,100)
```

R code Exa 4.15 Generating Halton low discrepancy sequences

```
1 #require (fBasics)
2 norm.interval = function(data, variance = var(data),
       conf.level = 0.95) {
     z = qnorm((1 - conf.level)/2, lower.tail = FALSE)
3
     xbar = mean(data)
     sdx = sqrt(variance/length(data))
     c(xbar - z * sdx, xbar + z * sdx)
6
7 }
8
9 BlsMCIS <- function(SO,K,r,T,sigma,NRepl) {
10
     nuT = (r - 0.5*sigma^2)*T;
     siT = sigma * sqrt(T);
11
12
     ISnuT = log(K/S0) - 0.5*sigma^2*T;
     Veps = rnorm(NRepl);
13
     VY = ISnuT + siT*Veps;
14
15
     ISRatios = exp((2*(nuT - ISnuT)*VY - nuT^2 +
        ISnuT^2)/2/siT^2);
     DiscPayoff = \exp(-r*T)*pmax(0, (S0*exp(VY)-K));
16
17
     parameter_estimation <-.normFit(DiscPayoff*ISRatios</pre>
     ci<-norm.interval(DiscPayoff*ISRatios)</pre>
18
     final <-list (parameter_estimation, ci)</pre>
19
     return(final)
20
21 }
22
23 Halton <- function(n,b) {
24
     n0 = n;
```

```
25
     h = 0;
26
     f = 1/b;
27
     while (n0 > 0){
28
       n1 = floor(n0/b);
29
       r = n0 - n1*b;
30
       h = h+f*r;
31
       f = f/b;
32
       n0=n1;
33
     }
34
     return(h)
35 }
36
37 \text{ seq} = \text{matrix}(0,10)
38 for (i in 1:10){
     seq[i] = Halton(i,2);
39
40 }
41
42 GetHalton <- function(HowMany, Base) {
     Seq = matrix(0, HowMany, 1)
43
     NumBits = 1+round(log(HowMany)/log(Base));
44
45
     VetBase = Base^(-(1:NumBits));
     WorkVet = matrix(0,1,NumBits);
46
     for (i in 1:HowMany){
47
       j = 1;
48
        ok = 0;
49
       while (ok == 0) {
50
51
          WorkVet[j] = WorkVet[j]+1;
52
          if (WorkVet[j] < Base){</pre>
53
            ok = 1;
          }
54
55
          else{
            WorkVet[j] = 0;
56
57
            j = j+1;
          }
58
59
60
       Seq[i] = sum(WorkVet * VetBase)
61
62
     return(Seq)
```

```
63 }
64
65
66
67 plot(runif(100), runif(100))
68 plot(GetHalton(100,2), GetHalton(100,7))
69 plot(GetHalton(100,2), GetHalton(100,4))
```

R code Exa 4.16 Generating Halton low discrepancy sequences

```
1 require(pracma)
2 f \leftarrow function(x,y) {
     exp(-x*y) *(sin(6*pi*x)+cos(8*pi*y))
4 }
6 \text{ dblquad}(f = f,xa = 0,xb = 1,ya = 0,yb = 1)
8 \text{ n} \leftarrow \text{seq}(0,1,0.01)
9 multiarray = list();
10 multiarray <- meshgrid(n,n)
11 Z<-f(multiarray$X,multiarray$Y)</pre>
12
13
14 persp(multiarray $X[1,],multiarray $Y[,1],Z,theta=30,
      phi=30, expand=0.6, col='lightblue', shade=0.75,
      ltheta=120,ticktype='detailed')
15
16 set.seed (4837)
17 mean(f(runif(10000),runif(10000)))
18 mean(f(runif(10000),runif(10000)))
19 mean(f(runif(10000),runif(10000)))
20
21 GetHalton <- function(HowMany, Base) {
22
     Seq = matrix(0, HowMany, 1)
23
     NumBits = 1+round(log(HowMany)/log(Base));
```

```
VetBase = Base^(-(1:NumBits));
24
     WorkVet = matrix(0,1,NumBits);
25
      for (i in 1:HowMany){
26
        j = 1;
27
28
        ok = 0;
        while (ok == 0){
29
          WorkVet[j] = WorkVet[j]+1;
30
          if (WorkVet[j] < Base){</pre>
31
32
             ok = 1;
33
          }
34
          else{
35
             WorkVet[j] = 0;
36
             j = j+1;
          }
37
        }
38
39
        Seq[i] = sum(WorkVet * VetBase)
40
41
     return (Seq)
42 }
43
44 \text{ seq2} = \text{GetHalton}(10000,2)
45 \text{ seq4} = \text{GetHalton}(10000,4)
46 \text{ seq5} = \text{GetHalton}(10000,5)
47 \text{ seq7} = \text{GetHalton}(10000,7)
48 \text{ mean} (f(seq2, seq5))
49 \text{ mean} (f(seq2, seq4))
50 \text{ mean}(f(seq2, seq7))
51 mean(f(seq5,seq7))
53 set.seed(327439)
54 mean(f(runif(100),runif(100)))
55 mean(f(runif(500),runif(500)))
56 mean(f(runif(1000),runif(1000)))
57 mean(f(runif(1500),runif(1500)))
58 mean(f(runif(2000),runif(2000)))
59
60 mean(f(seq2[1:100],seq7[1:100]))
61 mean(f(seq2[1:500],seq7[1:500]))
```

```
62 mean(f(seq2[1:1000],seq7[1:1000]))
63 mean(f(seq2[1:1500],seq7[1:1500]))
64 mean(f(seq2[1:2000],seq7[1:2000]))
```

R code Exa 4.17 Generating Halton low discrepancy sequences

```
1 require(pracma)
2 require(fBasics)
3 norm.interval = function(data, variance = var(data),
       conf.level = 0.95) {
     z = qnorm((1 - conf.level)/2, lower.tail = FALSE)
     xbar = mean(data)
     sdx = sqrt(variance/length(data))
7
     c(xbar - z * sdx, xbar + z * sdx)
8 }
9
10 GetHalton <- function(HowMany, Base) {</pre>
     Seq = matrix(0, HowMany, 1)
11
     NumBits = 1+round(log(HowMany)/log(Base));
12
13
     VetBase = Base^(-(1:NumBits));
14
     WorkVet = matrix(0,1,NumBits);
     for (i in 1:HowMany){
15
       j = 1;
16
17
       ok = 0;
       while (ok == 0) {
18
         WorkVet[j] = WorkVet[j]+1;
19
20
         if (WorkVet[j] < Base){</pre>
21
           ok = 1:
22
         }
         else{
23
24
           WorkVet[j] = 0;
25
           j = j+1;
         }
26
27
28
       Seq[i] = sum(WorkVet * VetBase)
```

```
29
     }
30
     return(Seq)
31 }
32
33 BlsHaltonBM <- function(SO,K,r,T,sigma,NPoints,Base1
      ,Base2) {
     nuT = (r - 0.5*sigma^2)*T;
34
     siT = sigma * sqrt(T);
35
     H1 = GetHalton(ceiling(NPoints/2), Base1);
36
     H2 = GetHalton(ceiling(NPoints/2), Base2);
37
     VLog = sqrt(-2*log(H1))
38
     Norm1 = VLog * cos(2*pi*H2)
39
40
     Norm2 = VLog * sin(2*pi*H2)
     Norm = rbind(Norm1, Norm2)
41
     DiscPayoff = exp(-r*T) * pmax(0, S0*exp(nuT+siT*))
42
        Norm) - K);
     Price = mean(DiscPayoff);
43
     return(Price)
44
45 }
46
47 BlsHaltonBM (50,52,0.1,5/12,0.4,5000,2,7)
48 BlsHaltonBM (50,52,0.1,5/12,0.4,5000,11,7)
49 BlsHaltonBM (50,52,0.1,5/12,0.4,5000,2,4)
50
51 BlsMC2 <- function(SO,K,r,T,sigma,NRepl) {
52
     nuT = (r - 0.5*sigma^2)*T;
53
     siT = sigma * sqrt(T);
     DiscPayoff = exp(-r*T)*pmax(0, S0*exp(nuT+siT*
54
        rnorm(NRepl))-K);
     parameter_estimation <-.normFit(DiscPayoff)</pre>
55
     ci<-norm.interval(DiscPayoff)</pre>
     final <-list (parameter_estimation, ci)</pre>
57
     return(final)
58
59 }
60
61 set.seed (3726)
62 BlsMC2(50,52,0.1,5/12,0.4,5000)
63 BlsMC2(50,52,0.1,5/12,0.4,5000)
```

```
64 BlsMC2(50,52,0.1,5/12,0.4,5000)
65
66 BlsHaltonINV <- function(SO,X,r,T,sigma,NPoints,Base
     ) {
67
     nuT = (r - 0.5*sigma^2)*T;
     siT = sigma * sqrt(T);
68
69
     # Use inverse transform to generate standard
        normals
     H = GetHalton(NPoints, Base);
70
     Veps = qnorm(H);
71
     DiscPayoff = \exp(-r*T)*pmax(0,S0*exp(nuT+siT*Veps)
72
     Price = mean(DiscPayoff);
73
     return(Price)
74
75 }
76
77 BlsHaltonINV (50,52,0.1,5/12,0.4,1000,2)
78 BlsHaltonINV (50,52,0.1,5/12,0.4,2000,2)
79 BlsHaltonINV(50,52,0.1,5/12,0.4,5000,2)
80 BlsHaltonINV (50,52,0.1,5/12,0.4,1000,2)
81 BlsHaltonINV (50,52,0.1,5/12,0.4,10000,2)
82 BlsHaltonINV (50,52,0.1,5/12,0.4,50000,2)
83
84 GetHalton (17,17)
85
86 BlsHaltonINV (50,52,0.1,5/12,0.4,1000,499)
87 BlsHaltonINV (50,52,0.1,5/12,0.4,2000,499)
88 BlsHaltonINV (50,52,0.1,5/12,0.4,5000,499)
89 BlsHaltonINV(50,52 ,0.1,5/12,0.4,10000,499)
90 BlsHaltonINV (50,52,0.1,5/12,0.4,50000,499)
91
92 plot (GetHalton (1000, 109), GetHalton (1000, 113))
```

R code Exa 4.18 Generating Sobol low discrepancy sequences

```
1 require(bitops)
2 GetDirNumbers <- function(p,m0,n) {</pre>
     degree = length(p)-1;
     p = p[2:degree];
4
5
     m = cbind(m0 , matrix(0,1,n-degree))
6
     for (i in (degree+1):n){
       m[i] = bitXor(m[i-degree], 2^degree * m[i-degree
7
           ])
        for (j in 1:(degree-1)){
8
          m[i] = bitXor(m[i], 2^j * p[j] * m[i-j]);
9
        }
10
11
12
     v=m/(2^{(1:length(m))})
     final<-list()</pre>
13
     final$v<-v
14
     final$m<-m
15
16 return(final)
17 }
18
19 p <-matrix(c(1,0, 1, 1), nrow = 1, ncol = 4)
20 \text{ m0} < -\text{matrix}(c(1,3, 7), \text{nrow} = 1, \text{ncol} = 3)
21 ans <- GetDirNumbers (p, m0, 6)
22 \text{ ans} \$v
23 \quad ans $m
```

R code Exa 4.19 Generating Sobol low discrepancy sequences

```
1 require(bitops)
2 gray<-function(x) bitXor(x,bitShiftR(x,1))
3 codes = matrix(0,16,4);
4 for (i in 1:16){
5  print(intToBits(gray(i-1)) [4:1])
6 }</pre>
```

${f R}$ code ${f Exa}$ 4.20 Generating Sobol low discrepancy sequences

```
1 require(bitops)
2 options(warn=-1)
4 GetDirNumbers <- function(p,m0,n) {
     degree = length(p)-1;
     p = p[2:degree];
6
     m = cbind(m0 , matrix(0,1,n-degree))
     for (i in (degree+1):n){
       m[i] = bitXor(m[i-degree], 2^degree * m[i-degree
9
          ])
10
       for (j in 1:(degree-1)){
          m[i] = bitXor(m[i], 2^j * p[j] * m[i-j]);
11
12
       }
13
     }
     v=m/(2^{(1:length(m))})
14
15
     final<-list()</pre>
16
     final$v<-v
     final$m<-m
17
     return(final)
18
19 }
20
21 p < -matrix(c(1,0, 1, 1), nrow = 1, ncol = 4)
22 \text{ m0} < -\text{matrix}(c(1,3, 7), \text{nrow} = 1, \text{ncol} = 3)
23 ans <- GetDirNumbers (p, m0, 6)
24 \text{ ans} \$v
25 \text{ ans} \$m
26
27 GetSobol <- function(GenNumbers, x0, HowMany) {
     Nbits = 20;
28
29
     factor = 2^Nbits;
     BitNumbers = GenNumbers * factor;
30
31
     SobSeq = matrix(0, HowMany + 1, 1);
```

```
32
     SobSeq[1] = as.integer(x0*factor);
     for (i in 1:HowMany){
33
       c = pmin(which( intToBits(i-1) [1:16] == 0 ));
34
       SobSeq[i+1] = bitXor(SobSeq[i], BitNumbers[c]);
35
36
37
     SobSeq = SobSeq / factor;
     return(SobSeq)
38
39 }
40 GetSobol(ans$v,0,10)
41
42
43 p \leftarrowmatrix(c(1,0, 1, 1,1,1),nrow = 1,ncol = 6)
44 m0 <-matrix(c(1,3, 5, 9, 11), nrow = 1, ncol = 5)
45 ans <- GetDirNumbers (p, m0, 10)
46
47 GetSobol(ans$v,0.124,10)
```

Chapter 5

Finite Difference Methods for Partial Differential Equations

R code Exa 5.1 Instability in a finite difference scheme

```
1 require(PopED)
3 transport <- function(xmin, dx, xmax, dt, tmax, c,
     f0) {
     N = ceiling((xmax - xmin) / dx);
     xmax = xmin + N*dx;
    M = ceiling(tmax/dt);
     k1 = 1 - dt*c/dx;
    k2 = dt*c/dx;
     solution = matrix(0, N+1, M+1);
10
     vetx = seq(xmin, xmax, dx)
     for (i in 1:N+1) {
11
       solution[i,1] = feval(f0,vetx[i]);
12
13
14
    fixedvalue = solution[1,1];
    # this is needed because of finite domain
15
    plot(solution[,1])
16
    for (j in 1:M){
17
       solution[,j+1] = k1*solution[,j] + k2*c(
```

```
fixedvalue, solution[1:N,j]);
19
       lines(solution[,j])
20
21
     return(solution)
22 }
23
24 fOtransp <- function(x) {
     if(x < (-1)){
25
26
       y = 0
27
     else if (x <= 0){
       y = x + 1;
28
29
     } else{
30
       y = 1;
     }
31
32 }
33
34 \text{ xmin} = -2;
35 \times max = 3;
36 dx = 0.05;
37 \text{ tmax} = 2;
38 \, dt = 0.01;
39 c = 1;
40 sol = transport(xmin, dx, xmax, dt, tmax, c,
      f0transp)
41
  TransportPlot <- function(xmin, dx, xmax, times, sol
      ) {
     par(mfrow=c(2,2))
43
     plot(seq(xmin,xmax,dx), sol[,times[1]])
44
     lines(seq(xmin,xmax,dx), sol[,times[1]])
45
     plot(seq(xmin, xmax, dx), sol[, times[2]])
46
     lines(seq(xmin,xmax,dx), sol[,times[2]])
47
48
     plot(seq(xmin,xmax,dx), sol[,times[3]])
     lines(seq(xmin, xmax, dx), sol[, times[3]])
49
     plot(seq(xmin,xmax,dx), sol[,times[4]])
50
     lines(seq(xmin,xmax,dx), sol[,times[4]])
51
52 }
53
```

```
54 TransportPlot(xmin, dx, xmax, c(1, 51, 101, 201),
     sol)
55
56 dx = 0.01
57 sol = transport(xmin, dx, xmax, dt, tmax, c,
     f0transp)
  TransportPlot(xmin, dx, xmax, c(1, 51, 101, 201),
58
     sol)
59
60 #Blow-outs
61 dx = 0.005
62 sol = transport(xmin, dx, xmax, dt, tmax, c,
     f0transp)
63 TransportPlot(xmin, dx, xmax, c(1, 51, 101, 201),
     sol)
```

R code Exa 5.3 Solving the heat equation by an explicit method

```
1 HeatExpl <- function(deltax, deltat, tmax) {</pre>
2
     N = round(1/deltax)
3
     M = round(tmax/deltat)
4
     sol = matrix(0, N+1, M+1)
     rho = deltat / (deltax)^2
5
6
     rho2 = 1-2*rho
7
     vetx = seq(0,1,deltax)
     for (i in 2: ceiling((N+1)/2)){
8
9
       sol[i,1] = 2*vetx[i]
       sol[N+2-i,1] = sol[i,1]
10
11
     }
     for (j in 1:M){
12
13
       for (i in 2:N){
14
         sol[i,j+1] = rho*sol[i-1,j] + rho2*sol[i,j] +
            rho*sol[i+1,j]
       }
15
16
     }
```

```
return(sol)
17
18 }
19
20 dx = 0.1;
21 	 dt = 0.001;
22 \text{ tmax} = dt*100;
23 sol=HeatExpl(dx, dt , tmax)
24
25 \text{ par}(\text{mfrow}=c(2,2))
26 plot(seq(0,1,dx), sol[,1])
27 lines(seq(0,1,dx), sol[,1])
28 \text{ plot}(seq(0,1,dx), sol[,11])
29 lines(seq(0,1,dx), sol[,11])
30 \text{ plot}(seq(0,1,dx), sol[,51])
31 \text{ lines}(seq(0,1,dx), sol[,51])
32 plot(seq(0,1,dx), sol[,101])
33 lines(seq(0,1,dx), sol[,101])
```

R code Exa 5.4 Solving the heat equation by a fully implicit method

```
1 HeatImpl <- function(deltax, deltat, tmax) {</pre>
2
     N = round(1/deltax)
     M = round(tmax/deltat)
3
4
     sol = matrix(0,N+1,M+1)
     rho = deltat / (deltax)^2
5
     B = diag(c((1+2*rho) * array(1, c(N-1,1)))) - diag(
6
        c(0,rho*array(1,c(N-1,1))))[2:100,1:99] - diag(
        c(0, rho*array(1, c(N-1,1))))[1:99, 2:100]
7
     vetx = seq(0,1,deltax)
8
     for (i in 2: ceiling((N+1)/2)){
       sol[i,1] = 2*vetx[i]
9
10
       sol[N+2-i,1] = sol[i,1]
     }
11
12
     for (j in 1:M){
13
       sol[2:N,j+1] = solve(B,sol[2:N,j])
```

```
14
     }
     return(sol)
15
16 }
17
18 \text{ deltax=dx=0.01}
19 deltat=dt=0.001
20 \quad tmax = dt * 100
21 sol=HeatImpl(dx,dt,tmax)
22
23 par(mfrow=c(2,2))
24 plot(seq(0,1,dx),sol[,1])
25 lines(seq(0,1,dx),sol[,1])
26 plot(seq(0,1,dx),sol[,11])
27 lines(seq(0,1,dx),sol[,11])
28 plot(seq(0,1,dx),sol[,51])
29 lines(seq(0,1,dx),sol[,51])
30 plot(seq(0,1,dx),sol[,101])
31 lines(seq(0,1,dx),sol[,101])
```

Chapter 6

Convex Optimization

R code Exa 6.1 Finite vs infinite dimensional problems

```
1 require(signal)
2 require("ucminf")
4 g <- function(x) {
     polyval(c(1, -10.5, 39, -59.5, 30), x)
6 }
7 \text{ xvet} = seq(1,4,0.05)
8 plot(xvet,g(xvet))
9 lines(xvet,g(xvet))
10
11 x \leftarrow ucminf(c(0),g) par
12 x
13 fval \leftarrow ucminf(c(0),g) value
14 fval
15
16 x \leftarrow ucminf(c(5),g) $par
18 fval <-ucminf(c(5),g)$value
19 fval
20
21 f \leftarrow function(x) {
```

```
22  polyval(c(1, -8, 22, -24, 1), x)
23 }
24  xvet=seq(0,4,0.05)
25  plot(xvet,f(xvet))
26  lines(xvet,f(xvet))
```

R code Exa 6.3 Linear vs non linear problems

```
1 require(lpSolve)
2 f.obj <- c(2, 3, 3)
3 f.con <- matrix (c(1, 2, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1), nrow=5, byrow=TRUE)
4 f.dir <- c("=", ">=", ">=", ">=", ">=", ">=")
5 f.rhs <- c(3, 3, 0, 0, 0)
6 lpSolve::lp(direction = "min",objective.in = f.obj, const.mat = f.con,const.dir = f.dir,const.rhs = f.rhs)</pre>
```

R code Exa 6.5 Penalty function approach

```
1 require(pracma)
2 f <- function(sigma,x,y) {
3   (x-1.5)^2+(y-0.5)^2+sigma/(1-x)+sigma/(1-y)
4 }
5 X<-meshgrid(x = seq(0.1,.99,.01))$X
6 Y<-meshgrid(x = seq(0.1,.99,.01))$Y
7 contour(f(0.1,X,Y))
8 contour(f(0.01,X,Y))
9 contour(f(0.001,X,Y))
10 contour(f(0.0001,X,Y))</pre>
```

R code Exa 6.8 Kuhn Tucker conditions

```
1 require(quadprog)
2 H = 2*eye(2)
3 f <-c(0,0)
4 Aeq <-matrix(c(1,1),nrow = 1)
5 beq <-4
6 lb <-matrix(c(0,3),ncol =1,nrow = 2)
7 quadprog(C = H,d = f,Aeq = Aeq,beq = beq,lb = lb)$
xmin</pre>
```

R code Exa 6.12 Geometric and algebraic features of linear programming

```
1 A \leftarrow matrix(data=c(-1, 1, 1, -1, 0, 0, 1, 0, 4, 0,
      0, 0, 2, 2, 1), nrow=3, ncol=5, byrow=TRUE)
2 b <- matrix(data=c(1, 3, 1), nrow=3, ncol=1, byrow=</pre>
      FALSE)
3 \text{ asvd} = \text{svd}(A)
4 adiag = diag(1/asvd$d)
5 solution = asvd$v %*% adiag %*% t(asvd$u) %*% b
6 Check = A %*% solution
8 # This solution does not match with the book,
9 # but in any case it's NOT FEASIBLE either as values
       present are less than ZERO
10
11 # Book solution check
12 X \leftarrow \text{matrix}(\text{data} = c(0,3,-2,0,5), \text{nrow} = 5, \text{ncol} = 1,
      byrow = TRUE)
13 A %*% X
```

Chapter 7

Option Pricing by Binomial and Trinomial Lattices

R code Exa 7.1 Calibrating a binomial lattice

```
1 LatticeEurCall <- function(SO,K,r,T,sigma,N) {</pre>
     deltaT = T/N
3
     u=exp(sigma * sqrt(deltaT))
     d=1/u
     p = (exp(r*deltaT) - d)/(u-d)
     lattice = matrix(0, N+1, N+1)
    for(i in 0:N){
8
       lattice[i+1,N+1]=\max(0,S0*(u^i)*(d^(N-i))-K)
9
     for(j in (N-1):0){
10
11
       for (i in 0:j){
12
         lattice[i+1,j+1] = \exp(-r*deltaT) * (p *
            lattice[i+2,j+2] + (1-p) * lattice[i+1,j
            +2])
       }
13
14
     }
     return(lattice[1,1])
15
16 }
17 call=LatticeEurCall(50,50,0.1,5/12,0.4,5)
```

```
18 call
19 call=LatticeEurCall(50,50,0.1,5/12,0.4,500)
20 call
```

R code Exa 7.2 Accuracy of the binomial lattice for decreasing deltaT

```
1 require(OptionPricing)
2 LatticeEurCall <- function(SO,K,r,T,sigma,N) {</pre>
     deltaT = T/N
3
     u=exp(sigma * sqrt(deltaT))
4
     d=1/u
5
     p = (exp(r*deltaT) - d)/(u-d)
6
     lattice = matrix(0, N+1, N+1)
8
     for(i in 0:N){
9
       lattice [i+1,N+1] = \max(0,S0*(u^i)*(d^(N-i))-K)
10
     for(j in (N-1):0){
11
       for (i in 0:j){
12
         lattice[i+1,j+1] = exp(-r*deltaT) * (p *
13
            lattice [i+2,j+2] + (1-p) * lattice [i+1,j]
            +2])
       }
14
15
16
     return(lattice[1,1])
17 }
18 \ SO = 50
19 K = 50
20 r = 0.1
21 \text{ sigma} = 0.4
22 T = 5/12
23 N = 50
24 BlsC = BS_EC(K = K, r = r, sigma = sigma, T = T, S0
      = S0)['price']
25 LatticeC = matrix(0,1,N)
26 for (i in 1:N){
```

R code Exa 7.3 Price a pay later option by a binomial lattice

```
1 require(pracma)
2 L11 <- function(premium,S0,K,r,sigma,T,N) {</pre>
     deltaT = T/N
     u=exp(sigma * sqrt (deltaT))
5
     d=1/u
     p = (exp(r*deltaT) - d)/(u-d)
     lattice = matrix(0, N+1, N+1)
7
8
     for (i in 0:N){
       if (S0*(u^i)*(d^(N-i)) >= K){
9
         lattice [i+1,N+1] = S0*(u^i)*(d^(N-i)) - K -
10
            premium
11
       }
12
     for (j in (N-1):0){
13
       for (i in 0:j){
14
         lattice[i+1, j+1] = p*lattice[<math>i+2, j+2] + (1-p)
15
            )*lattice[i+1, j+2]
16
       }
17
18
     return(lattice[1,1])
19 }
20
21 f <- function(P) {
     L11(premium = P,S0 = 12,K = 14,r = 0.1, sigma =
        0.2, T = 10/12, N = 10
23 }
```

R code Exa 7.4 Pricing an European call by a binomial lattice

```
1 require(OptionPricing)
2 require(tictoc)
3 LatticeEurCall <- function(SO,K,r,T,sigma,N) {</pre>
     deltaT = T/N
     u=exp(sigma * sqrt(deltaT))
5
     d=1/u
6
     p=(exp(r*deltaT) - d)/(u-d)
     lattice = matrix(0,N+1,N+1)
8
     for(i in 0:N){
10
       lattice [i+1,N+1] = \max(0,S0*(u^i)*(d^(N-i))-K)
11
     for(j in (N-1):0){
12
       for (i in 0:j){
13
         lattice[i+1,j+1] = \exp(-r*deltaT) * (p *
14
            lattice[i+2,j+2] + (1-p) * lattice[i+1,j
            +21)
15
       }
16
17
     return(lattice[1,1])
18 }
19 SmartEurLattice <- function(SO,K,r,T,sigma,N) {
     # Precompute invariant quantities
20
     deltaT = T/N
21
22
     u=exp(sigma * sqrt(deltaT))
23
     d=1/u
     p = (exp(r*deltaT) - d)/(u-d)
24
     discount = exp(-r*deltaT)
25
26
     p_u = discount*p
     p_d = discount*(1-p)
27
28
     # set up S values
     SVals = matrix(0,2*N+1,1)
29
```

```
SVals[1] = S0*d^N
30
31
     for (i in 2:(2*N+1)){
       SVals[i] = u*SVals[i-1]
32
33
     }
34
     # set up terminal CALL values
35
     CVals = matrix(0,2*N+1,1)
     for (i in seq(1,2*N+1,2)){
36
       CVals[i] = max(SVals[i]-K,0)
37
38
     }
    # work backwards
39
     for (tau in 1:N){
40
       for (i in seq((tau+1),(2*N+1-tau),2)){
41
42
         CVals[i] = p_u*CVals[i+1] + p_d*CVals[i-1]
       }
43
44
     }
45
     return (CVals [N+1])
46 }
47 tic()
48 BS_EC(SO = 50, K = 50, r = 0.1, sigma = 0.4, T = 5/
      12) ['price']
49 toc()
50
51 tic()
52 LatticeEurCall(SO = 50, K = 50, r = 0.1, sigma =
      0.4, T = 5/12, N = 2000)
53 toc()
54
55 tic()
56 SmartEurLattice(S0 = 50, K = 50, r = 0.1, sigma =
      0.4, T = 5/12, N = 2000)
57 toc()
```

R code Exa 7.5 Pricing an American put by a binomial lattice

```
1 AmPutLattice <- function(S0,K,r,T,sigma,N) {</pre>
```

```
2
     # Precompute invariant quantities
3
     deltaT = T/N
     u=exp(sigma * sqrt(deltaT))
4
     d=1/u
5
6
     p = (exp(r*deltaT) - d)/(u-d)
7
     discount = exp(-r*deltaT)
8
     p_u = discount*p
     p_d = discount*(1-p)
9
10
     # set up S values
     SVals = matrix(0,2*N+1,1)
11
     SVals[N+1] = S0
12
13
     for (i in 1:N){
14
       SVals[N+1+i] = u*SVals[N+i]
       SVals[N+1-i] = d*SVals[N+2-i]
15
     }
16
17
    # set up terminal values
     PVals = matrix(0,2*N+1,1)
18
19
     for (i in seq(1,2*N+1,2)){
20
       PVals[i] = max(K-SVals[i],0)
21
     }
22
     # work backwards
23
     for (tau in 1:N){
       for (i in seq((tau+1),(2*N+1-tau),2)){}
24
         hold = p_u*PVals[i+1] + p_d*PVals[i-1]
25
         PVals[i] = max(hold, K-SVals[i])
26
       }
27
28
29
     return(PVals[N+1])
30 }
31
32 AmPutLattice(S0 = 50, K = 50, r = 0.05, T = 5/12, sigma
       = 0.4, N = 1000)
```

R code Exa 7.6 Pricing an American spread option by a bidimensional binomial lattice

```
1 AmSpreadLattice <- function(S10,S20,K,r,T,sigma1,</pre>
      sigma2, rho, q1, q2, N) {
     # Precompute invariant quantities
2
3
     deltaT = T/N
4
     nu1 = r - q1 - 0.5*sigma1^2
5
     nu2 = r - q2 - 0.5*sigma2^2
6
     u1 = exp(sigma1*sqrt(deltaT))
7
     d1 = 1/u1
8
     u2 = exp(sigma2*sqrt(deltaT))
9
     d2 = 1/u2
10
     discount = exp(-r*deltaT)
11
     p_uu = discount*0.25*(1 + sqrt(deltaT)*(nu1/sigma1
         + nu2/sigma2) + rho)
12
     p_ud = discount*0.25*(1 + sqrt(deltaT)*(nu1/sigma1
         - nu2/sigma2) - rho)
     p_du = discount*0.25*(1 + sqrt(deltaT)*(-nu1/
13
        sigma1 + nu2/sigma2) - rho)
14
     p_dd = discount*0.25*(1 + sqrt(deltaT)*(-nu1/
        sigma1 - nu2/sigma2) + rho)
     # set up S values
15
16
     S1vals = matrix(0,2*N+1,1)
     S2vals = matrix(0,2*N+1,1)
17
     S1vals[1] = S10*d1^N
18
19
     S2vals[1] = S20*d2^N
20
     for (i in 2:(2*N+1)){
21
       S1vals[i] = u1*S1vals[i-1]
22
       S2vals[i] = u2*S2vals[i-1]
23
     }
24
     # set up terminal values
     Cvals = matrix(0,2*N+1,2*N+1)
25
     for (i in seq(1,2*N+1,2)){
26
       for (j in seq(1,2*N+1,2)){
27
28
         Cvals[i,j] = max(S1vals[i]-S2vals[j]-K,0)
       }
29
30
    # roll back
31
32
     for (tau in 1:N){
       for (i in seq((tau+1),(2*N+1-tau),2)){}
33
```

```
for (j in seq((tau+1),(2*N+1-tau),2)){
34
           hold = p_uu * Cvals[i+1,j+1] + p_ud * Cvals[
35
              i+1,j-1] + p_du * Cvals[i-1,j+1] + p_dd *
               Cvals[i-1, j-1]
           Cvals[i,j] = max(hold, S1vals[i] - S2vals[j]
36
               - K)
         }
37
       }
38
39
     return(Cvals[N+1,N+1])
40
41 }
42
43 AmSpreadLattice(S10 = 100, S20 = 100, K = 1, r =
     0.06, T = 1, sigma1 = 0.2, sigma2 = 0.3, rho =
     0.5, q1 = 0.03, q2 = 0.04, N = 3)
```

R code Exa 7.7 Pricing an European call by a trinomial lattice

```
1 require(OptionPricing)
2 EuCallTrinomial <- function(SO,K,r,T,sigma,N,deltaX)</pre>
3
    # Precompute invariant quantities
     deltaT = T/N
4
5
     nu = r - 0.5*sigma^2
     discount = exp(-r*deltaT)
     p_u = discount*0.5*((sigma^2*deltaT+nu^2*deltaT^2)
7
        /deltaX^2 + nu*deltaT/deltaX)
8
     p_m = discount*(1 - (sigma^2*deltaT+nu^2*deltaT^2)
       /deltaX^2)
9
     p_d = discount*0.5*((sigma^2*deltaT+nu^2*deltaT^2)
        /deltaX^2 - nu*deltaT/deltaX)
     # set up S values (at maturity)
10
     Svals = matrix(0,2*N+1,1)
11
12
     Svals[1] = S0*exp(-N*deltaX)
13
     exp_dX = exp(deltaX)
```

```
14
     for (j in 2:(2*N+1)){
15
       Svals[j] = exp_dX*Svals[j-1]
16
17
     # set up lattice and terminal values
18
     Cvals = matrix(0,2*N+1,2)
19
     t = mod(N,2) + 1
     for (j in 1:(2*N+1)){
20
       Cvals[j,t] = max(Svals[j]-K,0)
21
22
23
     for (t in (N-1):0){
       know = mod(t, 2) + 1
24
       knext = mod(t+1,2)+1
25
26
       for (j in (N-t+1):(N+t+1)){
         Cvals[j,know] = p_d*Cvals[j-1,knext]+p_m*Cvals
27
             [j,knext]+p_u*Cvals[j+1,knext]
       }
28
29
     return(Cvals[N+1,1])
30
31 }
32 \text{ BS\_EC}(S0 = 100, K = 100, r = 0.06, sigma = 0.3, T =
      1) ['price']
33 EuCallTrinomial(S0 = 100, K = 100, r = 0.06, T = 1,
      sigma = 0.3, N = 3, deltaX = 0.2
34 \, \text{EuCallTrinomial}(\text{SO} = 100, K = 100, r = 0.06, T = 1,
      sigma = 0.3, N = 100, deltaX = 0.2
35 \text{ EuCallTrinomial}(S0 = 100, K = 100, r = 0.06, T = 1,
      sigma = 0.3, N = 100, deltaX = 0.5
36 \text{ EuCallTrinomial}(S0 = 100, K = 100, r = 0.06, T = 1,
      sigma = 0.3, N = 100, deltaX = 0.3*sqrt (1/100)
37 \text{ EuCallTrinomial}(S0 = 100, K = 100, r = 0.06, T = 1,
      sigma = 0.3, N = 1000, deltaX = 0.3*sqrt (1/1000)
      )
```

Chapter 8

Option Pricing by Monte Carlo Methods

R code Exa 8.1 Generate asset price paths by Monte Carlo simulation

```
1 AssetPaths <- function(S0, mu, sigma, T, NSteps, NRepl) {
     SPaths = matrix(0,NRepl, 1+NSteps)
3
     SPaths[,1] = S0
     dt = T/NSteps
     nudt = (mu-0.5*sigma^2)*dt
     sidt = sigma*sqrt(dt)
     for (i in 1:NRepl){
8
       for (j in 1:NSteps){
         SPaths[i,j+1] = SPaths[i,j] * exp(nudt + sidt*
            rnorm(1))
       }
10
11
12
     return(SPaths)
13 }
14 set.seed(37456)
15 paths=AssetPaths (50,0.1,0.3,1,365,3)
16 plot(1:length(paths[3,]), paths[3,], type = 'l')
17 lines(1:length(paths[1,]), paths[1,], type = 'l')
18 lines(1:length(paths[2,]), paths[2,], type = 'l')
```

R code Exa 8.2 Vectorized code to generate asset price paths

```
1 require(varbvs)
2 require(tictoc)
3 AssetPathsV <- function(SO, mu, sigma, T, NSteps, NRepl)
      {
     dt = T/NSteps
     nudt = (mu-0.5*sigma^2)*dt
6
     sidt = sigma*sqrt(dt)
     Increments = nudt + sidt*randn(NRepl, NSteps)
7
     LogPaths = apply(cbind(matrix(log(S0)*matrix(1,
        NRepl,1)), Increments),2, cumsum)
9
     SPaths = exp(LogPaths)
10
     SPaths[,1] = S0
     return(SPaths)
11
12 }
13 AssetPaths <- function(SO, mu, sigma, T, NSteps, NRepl) {
14
     SPaths = matrix(0, NRepl, 1+NSteps)
15
     SPaths[,1] = S0
16
     dt = T/NSteps
     nudt = (mu-0.5*sigma^2)*dt
17
18
     sidt = sigma*sqrt(dt)
     for (i in 1:NRepl){
19
20
       for (j in 1:NSteps){
         SPaths[i,j+1]=SPaths[i,j]*exp(nudt + sidt*
21
            rnorm(1))
22
       }
23
     }
     return(SPaths)
24
25 }
26 Paths = AssetPathsV(50,0.1,0.3,1,100,1000)
27
28 N = dim(Paths)[2]
29 for (i in 1:N){
```

```
30    plot(Paths[,i],type = 'l')
31 }
32
33    tic()
34    AssetPaths(50,0.1,0.3,1,100,1000)
35    toc()
36
37    tic()
38    AssetPathsV(50,0.1,0.3,1,100,1000)
39    toc()
```

R code Exa 8.3 Evaluating the cost of a stop loss hedging strategy

```
1 require(pracma)
2 require(tictoc)
3 StopLoss <- function(S0,K,mu,sigma,r,T,Paths) {</pre>
     NRepl = dim(Paths)[1]
     NSteps = dim(Paths)[2]
5
6
     NSteps = NSteps - 1
7
     # true number of steps
8
     Cost = matrix(0,NRepl,1)
9
     dt = T/NSteps
     DiscountFactors = \exp(-r*(seq(0, NSteps, 1)*dt))
10
     for (k in 1:NRepl){
11
12
       CashFlows = matrix(0, NSteps+1,1)
       if (Paths[k,1] >= K){
13
14
         Covered = 1
         CashFlows[1] = -Paths[k,1]
15
16
       } else {
         Covered = 0
17
       }
18
       for (t in 2:(NSteps+1)){
19
20
         if ((Covered == 1) & (Paths[k,t] < K)){</pre>
21
           # Sell
22
           Covered = 0
```

```
23
            CashFlows[t] = Paths[k,t]
          } else if ((Covered == 0) & (Paths[k,t] > K)){
24
25
            # Buy
            Covered = 1
26
27
            CashFlows[t] = -Paths[k,t]
28
          }
       }
29
       if (Paths[k, NSteps + 1] >= K){
30
         # Option is exercised
31
32
          CashFlows[NSteps + 1] = CashFlows[NSteps + 1]
             + K
33
          }
34
       Cost[k] = - dot(DiscountFactors, CashFlows)
35
     return(mean(Cost))
36
37 }
38 AssetPaths <- function(SO, mu, sigma, T, NSteps, NRepl) {
39
     SPaths = matrix(0,NRepl, 1+NSteps)
     SPaths[,1] = S0
40
41
     dt = T/NSteps
42
     nudt = (mu-0.5*sigma^2)*dt
     sidt = sigma*sqrt(dt)
43
44
     for (i in 1:NRepl){
       for (j in 1:NSteps){
45
          SPaths[i,j+1]=SPaths[i,j]*exp(nudt + sidt*
46
             rnorm(1))
47
       }
48
     return(SPaths)
49
50 }
51 S0 = 50
52 \text{ K} = 50
53 \text{ mu} = 0.1
54 \text{ sigma} = 0.4
55 r = 0.05
56 T = 5/12
57 \text{ NRepl} = 100000
58 NSteps = 10
```

```
59  set.seed(39473)
60  Paths=AssetPaths(SO,mu, sigma,T,NSteps,NRepl)
61  tic()
62  StopLoss(SO,K,mu,sigma,r,T,Paths)
63  toc()
```

R code Exa 8.4 Vectorized code for the stop loss hedging strategy

```
1 require(pracma)
2 require(tictoc)
3 StopLoss <- function(S0,K,mu,sigma,r,T,Paths) {</pre>
     NRepl = dim(Paths)[1]
     NSteps = dim(Paths)[2]
5
6
     NSteps = NSteps - 1
     # true number of steps
     Cost = matrix(0,NRepl,1)
8
9
     dt = T/NSteps
     DiscountFactors = \exp(-r*(seq(0, NSteps, 1)*dt))
10
     for (k in 1:NRepl){
11
12
       CashFlows = matrix(0, NSteps+1,1)
13
       if (Paths[k,1] >= K){
14
         Covered = 1
15
         CashFlows[1] = -Paths[k,1]
       } else {
16
         Covered = 0
17
18
19
       for (t in 2:(NSteps+1)){
20
         if ((Covered == 1) & (Paths[k,t] < K)){</pre>
           # Sell
21
22
           Covered = 0
           CashFlows[t] = Paths[k,t]
23
         } else if ((Covered == 0) & (Paths[k,t] > K)){
24
25
           # Buy
26
           Covered = 1
27
           CashFlows[t] = -Paths[k,t]
```

```
}
28
        }
29
        if (Paths[k, NSteps + 1] >= K){
30
31
          # Option is exercised
32
          CashFlows[NSteps + 1] = CashFlows[NSteps + 1]
33
          }
        Cost[k] = - dot(DiscountFactors, CashFlows)
34
35
     return(mean(Cost))
36
37 }
38 AssetPaths <- function(SO, mu, sigma, T, NSteps, NRepl) {
39
     SPaths = matrix(0,NRepl, 1+NSteps)
     SPaths[,1] = S0
40
41
     dt = T/NSteps
     nudt = (mu-0.5*sigma^2)*dt
42
     sidt = sigma*sqrt(dt)
43
     for (i in 1:NRepl){
44
        for (j in 1:NSteps){
45
          SPaths[i,j+1] = SPaths[i,j] * exp(nudt + sidt*
46
             rnorm(1))
        }
47
48
     }
     return(SPaths)
49
50 }
51 \text{ SO} = 50
52 K = 50
53 \text{ mu} = 0.1
54 \text{ sigma} = 0.4
55 r = 0.05
56 T = 5/12
57 \text{ NRepl} = 100000
58 NSteps = 10
59 set.seed(39473)
60 Paths=AssetPaths(SO, mu, sigma, T, NSteps, NRepl)
61
62 StopLossV <- function(SO,K,mu,sigma,r,T,Paths) {
     NRepl = dim(Paths)[1]
63
```

```
64
     NSteps = dim(Paths)[2]
65
     NSteps = NSteps - 1
     Cost = matrix(0, NRepl,1)
66
     CashFlows = matrix(0,NRepl,NSteps+1)
67
68
     dt = T/NSteps
69
     DiscountFactors = \exp(-r*(seq(0, NSteps, 1))*dt)
     OldPrice = cbind(matrix(0, NRepl,1), Paths[,1:
70
        NSteps])
     UpTimes = which(OldPrice < K & Paths >= K)
71
     DownTimes = which(OldPrice >= K & Paths < K)</pre>
72
     CashFlows[UpTimes] = -Paths[UpTimes]
73
74
     CashFlows[DownTimes] = Paths[DownTimes]
75
     ExPaths = which(Paths[, NSteps+1] >= K)
     CashFlows[ExPaths, NSteps+1] = CashFlows[ExPaths,
76
        NSteps+1] + K
     Cost = -CashFlows %*%(matrix(DiscountFactors))
77
     return(mean(Cost))
78
79 }
80
81 tic()
82 StopLossV(SO,K,mu,sigma,r,T,Paths)
83 toc()
```

R code Exa 8.5 Evaluating the performance of delta hedging

```
10
     CashFlows = matrix(0,1,NSteps+1)
11
     dt = T/NSteps
12
     DiscountFactors = \exp(-r*(seq(0, NSteps, 1)*dt))
13
     for (i in 1:NRepl){
14
       Path = Paths[i,]
15
       Position = 0
16
       Deltas = matrix()
17
       for (k in 1:NSteps){
         Deltas[k] = f(T = T-(k-1)*dt, Path = Path[k])
18
19
       }
20
       for (j in 1:NSteps){
         CashFlows[j] = (Position - Deltas[j])*Path[j]
21
22
         Position = Deltas[j]
23
       }
24
       if (Path[NSteps+1] > K){
         CashFlows[NSteps+1] = K - (1-Position)*Path[
25
            NSteps+1]
26
       } else {
         CashFlows[NSteps+1] = Position*Path[NSteps+1]
27
       }
28
29
       Cost[i] = -CashFlows %*% DiscountFactors
30
31
     return(mean(Cost))
32 }
33
34 AssetPaths <- function(SO, mu, sigma, T, NSteps, NRepl) {
35
     SPaths = matrix(0,NRepl, 1+NSteps)
     SPaths[,1] = S0
36
37
     dt = T/NSteps
     nudt = (mu-0.5*sigma^2)*dt
38
39
     sidt = sigma*sqrt(dt)
     for (i in 1:NRepl){
40
41
       for (j in 1:NSteps){
         SPaths[i,j+1]=SPaths[i,j]*exp(nudt + sidt*
42
            rnorm(1))
       }
43
     }
44
     return(SPaths)
45
```

```
46 }
47
48 StopLossV <- function(SO,K,mu,sigma,r,T,Paths) {
     NRepl = dim(Paths)[1]
49
     NSteps = dim(Paths)[2]
50
     NSteps = NSteps - 1
51
     Cost = matrix(0,NRepl,1)
52
     CashFlows = matrix(0,NRepl,NSteps+1)
53
     dt = T/NSteps
54
     DiscountFactors = \exp(-r*(seq(0, NSteps, 1))*dt)
55
     OldPrice = cbind(matrix(0, NRepl,1), Paths[,1:
56
        NSteps])
57
     UpTimes = which(OldPrice < K & Paths >= K)
58
     DownTimes = which(OldPrice >= K & Paths < K)
     CashFlows[UpTimes] = -Paths[UpTimes]
59
     CashFlows[DownTimes] = Paths[DownTimes]
60
     ExPaths = which(Paths[, NSteps+1] >= K)
61
62
     CashFlows[ExPaths, NSteps+1] = CashFlows[ExPaths,
        NSteps+1] + K
     Cost = -CashFlows %*%(matrix(DiscountFactors))
63
     return(mean(Cost))
64
65 }
66
67 \text{ SO} = 50
68 K = 52
69 \text{ mu} = 0.1
70 \text{ sigma} = 0.4
71 r = 0.05
72 T = 5/12
73 \text{ NRepl} = 10000
74 NSteps = 10
75 C = BS_EC(K = K, r = r, sigma = sigma, T = T, SO = r)
      SO)['price']
76 set.seed(3872)
77 Paths=AssetPaths(SO,mu,sigma,T,NSteps,NRepl)
78 True_Price = BS_EC(SO = SO,K = K,r = r,sigma = sigma
      T = T ['price']
79 SL = StopLossV(SO,K,mu,sigma,r,T,Paths)
```

R code Exa 8.6 Implementing and checking path generation for the standard Wiener process by a Brownian bridge

```
WienerBridge <- function(T, NSteps) {</pre>
2
     NBisections = log2(NSteps)
     if (round(NBisections) != NBisections){
3
       cat ('ERROR in WienerBridge: NSteps must be a
4
          power of 2', \langle n' \rangle
       return
5
6
7
     WSamples = matrix(0, NSteps+1,1)
8
     WSamples[1] = 0
9
     WSamples[NSteps+1] = sqrt(T)*rnorm(1)
10
     TJump = T
     IJump = NSteps
11
     for (k in 1:NBisections){
12
13
       left = 1
14
       i = IJump/2 + 1
15
       right = IJump + 1
       for (j in 1:(2^{(k-1)})){
16
          a = 0.5*(WSamples[left] + WSamples[right])
17
18
          b = 0.5*sqrt(TJump)
19
          WSamples[i] = a + b*rnorm(1)
20
          right = right + IJump
21
          left = left + IJump
```

```
22
          i = i + IJump
23
        }
        IJump = IJump/2
24
25
        TJump = TJump/2
26
     return(WSamples)
27
28 }
29
30
31 # CheckBridge.m
32 set.seed (3826)
33 \text{ NRepl} = 100000
34 \text{ T} = 1
35 NSteps = 4
36 WSamples = matrix(0, NRepl, 1+NSteps)
37 for (i in 1:NRepl){
38
     WSamples[i,] =WienerBridge(T, NSteps)
39 }
40 a <- function(X) {
41
     mean(X)
42 }
43 \text{ b} \leftarrow \text{function}(X)  {
     sqrt(var(X))
44
45 }
46 m = matrix()
47 sdev = matrix()
48 for (z in 2:(1+NSteps)){
     m[z-1] = a(WSamples[,z])
49
      sdev[z-1] = b(WSamples[,z])
50
51 }
52 \, \mathrm{m}
53 sdev
54 sqrt((1:NSteps)*T/NSteps)
```

R code Exa 8.7 Code to price an exchange option analytically

```
1 require(lmom)
2 Exchange <- function(V0, U0, sigmaV, sigmaU, rho, T, r) {</pre>
     sigmahat = sqrt(sigmaU^2 + sigmaV^2 - 2*rho*sigmaU
        *sigmaV)
     d1 = (log(V0/U0) + 0.5*T*sigmahat^2)/(sigmahat*)
4
        sqrt(T))
     d2 = d1 - sigmahat*sqrt(T)
5
     p = V0*cdfnor(d1) - U0*cdfnor(d2)
     return(p)
8 }
9
10 \ VO = 50
11 \ UO = 60
12 \text{ sigmaV} = 0.3
13 \text{ sigmaU} = 0.4
14 \text{ rho} = 0.7
15 T = 5/12
16 r = 0.05
17 Exchange (VO , UO, sigmaV, sigmaU, rho, T ,r)
```

R code Exa 8.8 Code to price an exchange option by Monte Carlo simulation

```
NRepl) {
12
     eps1 = rnorm(NRepl)
     eps2 = rho*eps1 + sqrt(1-rho^2)*rnorm(NRepl)
13
     VT = V0*exp((r - 0.5*sigmaV^2)*T + sigmaV*sqrt(T)*
14
         eps1)
15
     UT = U0*exp((r - 0.5*sigmaU^2)*T + sigmaU*sqrt(T)*
         eps2)
     DiscPayoff = matrix()
16
17
     for(i in 1:length(VT)){
        DiscPayoff[i] = f(r,T,VT[i],UT[i])
18
19
20
     parameter_estimation <-.normFit(DiscPayoff)</pre>
21
     ci<-norm.interval(DiscPayoff)</pre>
     return(c(parameter_estimation,ci))
22
23 }
24 \text{ VO} = 50
25 \text{ UO} = 60
26 \text{ sigmaV} = 0.3
27 \text{ sigmaU} = 0.4
28 \text{ rho} = 0.7
29 T = 5/12
30 r = 0.05
31 \text{ NRepl} = 200000
32 ExchangeMC(VO, UO, sigmaV, sigmaU, rho, T, r, NRepl)
```

R code Exa 8.9 Crude Monte Carlo simulation for a discrete barrier option

```
1 require(OptionPricing)
2 AssetPaths <- function(S0,mu,sigma,T,NSteps,NRepl) {
3    SPaths = matrix(0,NRepl, 1+NSteps)
4    SPaths[,1] = S0
5    dt = T/NSteps
6    nudt = (mu-0.5*sigma^2)*dt
7    sidt = sigma*sqrt(dt)
8    for (i in 1:NRepl){</pre>
```

```
9
       for (j in 1:NSteps){
10
         SPaths[i,j+1]=SPaths[i,j]*exp(nudt + sidt*
            rnorm(1))
       }
11
12
     }
13
     return(SPaths)
14 }
15 norm.interval = function(data, variance = var(data),
       conf.level = 0.95) {
     z = qnorm((1 - conf.level)/2, lower.tail = FALSE)
16
     xbar = mean(data)
17
     sdx = sqrt(variance/length(data))
18
19
     c(xbar - z * sdx, xbar + z * sdx)
20 }
21 DOPutMC <-function(SO,K,r,T,sigma,Sb,NSteps,NRepl){
22
     # Generate asset paths
     Call = BS_EC(SO,K,r,T,sigma)
23
     Put = BS_EP(S0,K,r,T,sigma)
24
     Payoff = matrix(0, NRepl, 1)
25
     NCrossed = 0
26
27
     for (i in 1:NRepl){
       Path=AssetPaths(S0,r,sigma,T,NSteps,1)
28
29
       crossed = any(Path <= Sb)</pre>
       if (crossed == 0){
30
         Payoff[i] = max(0, K - Path[NSteps+1])
31
32
       } else{
33
         Payoff[i] = 0
34
         NCrossed = NCrossed + 1
35
       }
     }
36
37
     parameter_estimation<-.normFit(exp(-r*T) * Payoff)</pre>
38
     ci<-norm.interval(exp(-r*T) * Payoff)</pre>
39
     return(c(parameter_estimation,ci))
40 }
41 DOPutMC (50,50,0.1,2/12,0.4,40,60,50000)
```

R code Exa 8.10 Conditional Monte Carlo simulation for a discrete barrier option

```
1 require(OptionPricing)
2 require(fBasics)
3 require(fOptions)
4 AssetPaths <- function(SO, mu, sigma, T, NSteps, NRepl) {
     SPaths = matrix(0,NRepl, 1+NSteps)
     SPaths[,1] = S0
6
7
     dt = T/NSteps
     nudt = (mu-0.5*sigma^2)*dt
9
     sidt = sigma*sqrt(dt)
10
     for (i in 1:NRepl){
       for (j in 1:NSteps){
11
12
         SPaths[i,j+1]=SPaths[i,j]*exp(nudt + sidt*
            rnorm(1))
13
       }
14
15
    return(SPaths)
16 }
17
18 norm.interval = function(data, variance = var(data),
       conf.level = 0.95) {
     z = qnorm((1 - conf.level)/2, lower.tail = FALSE)
19
20
     xbar = mean(data)
21
     sdx = sqrt(variance/length(data))
     c(xbar - z * sdx, xbar + z * sdx)
22
23 }
24
25 is.integer0 <- function(x)
26 {
27
    is.integer(x) && length(x) == OL
28 }
29
```

```
30 DOPutMCCond <- function(SO,K,r,T,sigma,Sb,NSteps,
      NRepl) {
     dt = T/NSteps;
31
     Call = GBSOption(TypeFlag = "c", S = SO, X = K,
32
        Time = T, r = r, sigma = sigma, b = r)
     Put = GBSOption(TypeFlag = "p", S = S0, X = K,
33
        Time = T, r = r, sigma = sigma, b = r)
     # Generate asset paths and payoffs for the down
34
        and in option
     NCrossed = 0
35
     Payoff = matrix(0, NRepl,1)
36
37
     Times = matrix(0,NRepl,1)
38
     StockVals = matrix(0,NRepl,1)
     for (i in 1:NRepl){
39
       Path=AssetPaths(SO,r,sigma,T,NSteps,1)
40
       tcrossed = pmin(which(Path <= Sb))
41
       if (!(is.integer0(tcrossed))){
42
         NCrossed = NCrossed + 1
43
         Times[NCrossed,] = (length(tcrossed) - 1) * dt
44
         StockVals[NCrossed,] = Path[,length(tcrossed)]
45
46
       }
     }
47
48
     Paux<-matrix()</pre>
     f <- function(SO,K,r,T,sigma) {
49
       GBSOption(TypeFlag = "p", S = S0, X = K, Time =
50
          T, r = r, sigma = sigma, b = r
51
     }
52
     if (NCrossed > 0){
       for (j in 1:NCrossed){
53
         Paux[j] = f(StockVals[j],K,r,(T-Times[j]),
54
            sigma) Oprice
         Payoff[j] = exp(-r*Times[j]) * Paux[j]
55
56
       }
57
     }
58
     parameter_estimation <-.normFit(Put@price - Payoff)</pre>
     ci<-norm.interval(Put@price - Payoff)</pre>
59
     return(c(parameter_estimation,ci,NCrossed))
60
61 }
```

R code Exa 8.11 Using conditional Monte Carlo and importance sampling for a discrete barrier option

```
1 require(OptionPricing)
2 require(fBasics)
3 require(fOptions)
4 require(varbvs)
5 AssetPaths <- function(SO, mu, sigma, T, NSteps, NRepl) {
     SPaths = matrix(0, NRepl, 1+NSteps)
7
     SPaths[,1] = S0
8
     dt = T/NSteps
     nudt = (mu-0.5*sigma^2)*dt
9
     sidt = sigma*sqrt(dt)
10
     for (i in 1:NRepl){
11
       for (j in 1:NSteps){
12
         SPaths[i,j+1] = SPaths[i,j] * exp(nudt + sidt*
13
            rnorm(1))
14
       }
15
     return(SPaths)
16
17 }
18
19 norm.interval = function(data, variance = var(data),
       conf.level = 0.95) {
20
     z = qnorm((1 - conf.level)/2, lower.tail = FALSE)
21
     xbar = mean(data)
     sdx = sqrt(variance/length(data))
     c(xbar - z * sdx, xbar + z * sdx)
23
24 }
25
26 is.integer0 <- function(x)
27 {
```

```
is.integer(x) && length(x) == OL
28
29 }
30
31 DOPutMCCondIS <- function(SO,K,r,T,sigma,Sb,NSteps,
      NRepl,bp){
32
     dt = T/NSteps
33
     nudt = (r-0.5*sigma^2)*dt
     b = bp*nudt
34
     sidt = sigma*sqrt(dt)
35
     Call = GBSOption(TypeFlag = "c", S = SO, X = K,
36
        Time = T, r = r, sigma = sigma, b = r)
     Put = GBSOption(TypeFlag = "p", S = SO, X = K,
37
        Time = T, r = r, sigma = sigma, b = r)
     # Generate asset paths and payoffs for the down
38
        and in option
     NCrossed = 0
39
     Payoff = matrix(0, NRepl,1)
40
     Times = matrix(0,NRepl,1)
41
     StockVals = matrix(0,NRepl,1)
42
43
     ISRatio = matrix(0,NRepl,1)
44
     for (i in 1:NRepl){
45
       # generate normals
46
       vetZ = nudt - b + sidt*randn(1, NSteps)
       LogPath = apply(cbind(log(S0), vetZ),1,cumsum)
47
       Path = exp(LogPath)
48
49
       jcrossed = pmin(which(Path <= Sb ))</pre>
50
       if (!(is.integer0(jcrossed))){
         jcrossed = min(jcrossed)
51
52
         NCrossed = NCrossed + 1
         TBreach = jcrossed - 1
53
54
         Times[NCrossed,] = TBreach * dt
       StockVals[NCrossed,] = Path[jcrossed]
55
56
         ISRatio[NCrossed,] = exp( TBreach*b^2/2/sigma
            ^2/dt + b/sigma^2/dt*sum(vetZ[1:TBreach]) -
             TBreach*b/sigma^2*(r - sigma^2/2))
       }
57
     }
58
     Paux <-matrix()</pre>
59
```

```
f <- function(S0,K,r,T,sigma) {</pre>
60
       GBSOption(TypeFlag = "p", S = SO, X = K, Time =
61
          T, r = r, sigma = sigma, b = r
62
     }
63
     if (NCrossed > 0){
64
       for (j in 1:NCrossed){
         Paux[j] = f(StockVals[j],K,r,(T-Times[j]),
65
            sigma) Oprice
         Payoff[j] = exp(-r*Times[j])* Paux[j] *
66
            ISRatio[j]
       }
67
68
     }
69
     parameter_estimation <-.normFit(Put@price - Payoff)</pre>
     ci<-norm.interval(Put@price - Payoff)</pre>
70
     return(c(parameter_estimation,ci,NCrossed))
71
72 }
73 DOPutMCCondIS (50,52,0.1,2/12,0.4,30,60,10000,0)
74 DOPutMCCondIS (50,52,0.1,2/12,0.4,30,60,10000,20)
75 DOPutMCCondIS (50,52,0.1,2/12,0.4,30,60,10000,50)
76 DOPutMCCondIS (50,52,0.1,2/12,0.4,30,60,10000,200)
```

R code Exa 8.12 Monte Carlo simulation for an Asian option

```
1 require(OptionPricing)
2 require(fBasics)
3 require(fOptions)
4 require(varbvs)
5 AssetPaths <- function(SO, mu, sigma, T, NSteps, NRepl) {
    SPaths = matrix(0,NRepl, 1+NSteps)
6
    SPaths[,1] = S0
7
    dt = T/NSteps
8
    nudt = (mu-0.5*sigma^2)*dt
    sidt = sigma*sqrt(dt)
10
     for (i in 1:NRepl){
11
12
       for (j in 1:NSteps){
```

```
13
          SPaths[i,j+1]=SPaths[i,j]*exp(nudt + sidt*
             rnorm(1))
14
       }
15
     }
16
     return(SPaths)
17 }
18 norm.interval = function(data, variance = var(data),
       conf.level = 0.95) {
     z = qnorm((1 - conf.level)/2, lower.tail = FALSE)
19
     xbar = mean(data)
20
     sdx = sqrt(variance/length(data))
21
22
     c(xbar - z * sdx, xbar + z * sdx)
23 }
24 AsianMC <-function(SO, K, r, T, sigma, NSamples, NRepl){
     Payoff = matrix(0, NRepl, 1)
25
     for (i in 1:NRepl){
26
       Path=AssetPaths(SO,r,sigma,T,NSamples,1)
27
28
       Payoff[i] = max(0, mean(Path[2:(NSamples+1)]) -
          K)
29
     }
30
     parameter_estimation<-.normFit(exp(-r*T) * Payoff)</pre>
     ci<-norm.interval(exp(-r*T) * Payoff)</pre>
31
     return(c(parameter_estimation,ci))
32
33 }
34 set.seed(28282)
35 \text{ X} \leftarrow \text{AsianMC} (50, 50, 0.1, 5/12, 0.4, 5, 50000)
36 X
37 X[[3]]-X[[2]]
```

 ${f R}$ code ${f Exa}$ 8.13 Monte Carlo simulation with control variates for an Asian option

```
1 require(OptionPricing)
2 require(fBasics)
3 require(fOptions)
```

```
4 require(varbvs)
5 AssetPaths <- function(S0, mu, sigma, T, NSteps, NRepl) {
     SPaths = matrix(0, NRepl, 1+NSteps)
     SPaths[,1] = S0
7
8
     dt = T/NSteps
     nudt = (mu-0.5*sigma^2)*dt
9
10
     sidt = sigma*sqrt(dt)
     for (i in 1:NRepl){
11
12
       for (j in 1:NSteps){
         SPaths[i,j+1]=SPaths[i,j]*exp(nudt + sidt*
13
            rnorm(1))
       }
14
15
     }
16
     return(SPaths)
17 }
18 norm.interval = function(data, variance = var(data),
       conf.level = 0.95) {
19
     z = qnorm((1 - conf.level)/2, lower.tail = FALSE)
     xbar = mean(data)
20
     sdx = sqrt(variance/length(data))
21
22
     c(xbar - z * sdx, xbar + z * sdx)
23 }
24 AsianMCCV <-function(SO,K,r,T,sigma,NSamples,NRepl,
      NPilot){
     # pilot replications to set control parameter
25
26
     TryPath = AssetPaths (SO, r, sigma, T, NSamples, NPilot)
27
     StockSum <-matrix()</pre>
     PP<-matrix()</pre>
28
     TryPayoff<-matrix()</pre>
29
     for (i in 1:length(TryPath[,1])){
30
       StockSum[i] = sum(TryPath[i,])
31
       PP[i] = mean(TryPath[i,2:(NSamples+1)])
32
33
       TryPayoff[i] = exp(-r*T) * max(0, PP[i] - K)
     }
34
     MatCov = cov(cbind(StockSum, TryPayoff))
35
     c = - MatCov[1,2] / var(StockSum)
36
37
     dt = T / NSamples
     ExpSum = S0 * (1 - exp((NSamples + 1)*r*dt)) / (1
38
```

```
- exp(r*dt))
39
     # MC run
     ControlVars = matrix(0,NRepl,1)
40
41
     for (i in 1:NRepl){
42
       StockPath = AssetPaths(S0,r,sigma,T,NSamples,1)
43
       Payoff = \exp(-r*T) * \max(0, \max(StockPath[2:(
          NSamples+1)]) - K)
       ControlVars[i] = Payoff + c * (sum(StockPath) -
44
          ExpSum)
45
     parameter_estimation <-.normFit(ControlVars)</pre>
46
     ci<-norm.interval(ControlVars)</pre>
47
48
     return(c(parameter_estimation,ci))
49 }
50 X <- Asian MCCV (50,50,0.1,5/12,0.4,5,45000,5000)
52 X[[3]]-X[[2]]
```

R code Exa 8.14 Using the geometric average Asian option as a control variate

```
1 require(OptionPricing)
2 require(fBasics)
3 require(fOptions)
4 require(varbvs)
5 require(lmom)
6 GeometricAsian <-function(SO,K,r,T,sigma,delta,
     NSamples) {
7
     dT = T/NSamples
     nu = r - sigma^2/2-delta
8
     a = log(S0) + nu*dT + 0.5*nu*(T-dT)
9
     b = sigma^2*dT + sigma^2*(T-dT)*(2*NSamples-1)/6/
10
        NSamples
11
     x = (a-log(K)+b)/sqrt(b)
12
     P = \exp(-r*T)*(\exp(a+b/2)*cdfnor(x) - K*cdfnor(x-
```

```
sqrt(b)))
13
     return(P)
14 }
15 norm.interval = function(data, variance = var(data),
       conf.level = 0.95) {
16
     z = qnorm((1 - conf.level)/2, lower.tail = FALSE)
17
     xbar = mean(data)
     sdx = sqrt(variance/length(data))
18
     c(xbar - z * sdx, xbar + z * sdx)
19
20 }
21 AssetPaths <- function(SO, mu, sigma, T, NSteps, NRepl) {
     SPaths = matrix(0,NRepl, 1+NSteps)
22
     SPaths[,1] = S0
23
     dt = T/NSteps
24
     nudt = (mu-0.5*sigma^2)*dt
25
     sidt = sigma*sqrt(dt)
26
     for (i in 1:NRepl){
27
28
       for (j in 1:NSteps){
         SPaths[i,j+1]=SPaths[i,j]*exp(nudt + sidt*
29
            rnorm(1))
30
       }
     }
31
32
     return(SPaths)
33 }
34 AsianMCGeoCV <-function(SO,K,r,T,sigma,NSamples,NRepl
      , NPilot) {
35
     # precompute quantities
     DF = \exp(-r*T)
36
     GeoExact = GeometricAsian(S0,K,r,T,sigma,0,
37
        NSamples)
     # pilot replications to set control parameter
38
     GeoPrices = matrix(0,NPilot,1)
39
40
     AriPrices = matrix(0, NPilot, 1)
     for (i in 1:NPilot){
41
       Path=AssetPaths(SO,r,sigma,T,NSamples,1)
42
       GeoPrices[i]=DF*max(0,(prod(Path[,2:(NSamples+1)
43
          ]))^(1/NSamples) - K)
       AriPrices[i] = DF * max(0, mean(Path[,2:(NSamples+1))
44
```

```
]) - K)
45
     MatCov = cov(cbind(GeoPrices, AriPrices))
46
     c = - MatCov[1,2] / var(GeoPrices)
47
48
     # MC run
49
     ControlVars = matrix(0,NRepl,1)
     for (i in 1:NRepl){
50
      Path = AssetPaths(SO,r,sigma,T,NSamples,1)
51
      GeoPrice = DF*max(0, (prod(Path[2:(NSamples+1)]))
52
         ^(1/NSamples) - K)
      AriPrice = DF*max(0, mean(Path[2:(NSamples+1)]) -
53
54
      ControlVars[i] = AriPrice + c * (GeoPrice -
         GeoExact)
55
     parameter_estimation <-. normFit (ControlVars)</pre>
56
     ci<-norm.interval(ControlVars)</pre>
57
     return(c(parameter_estimation,ci))
58
59 }
60 set.seed(2372)
61 \text{ SO} = 50
62 K = 55
63 r = 0.05
64 \text{ sigma} = 0.4
65 T = 1
66 NSamples = 12
67 \text{ NRepl} = 9000
68 NPilot = 1000
69 AsianMCGeoCV(SO,K,r,T,sigma,NSamples,NRepl,NPilot)
```

R code Exa 8.15 Pricing an Asian option by Halton sequences

```
1 require(gmp)
2 require(lmom)
3 require(lestat)
```

```
4
5 GetHalton <- function(HowMany, Base) {
     Seq = matrix(0, HowMany, 1)
     NumBits = 1+round(log(HowMany)/log(Base));
7
8
     VetBase = Base^(-(1:NumBits));
9
     WorkVet = matrix(0,1,NumBits);
10
     for (i in 1:HowMany){
11
       j = 1;
12
       ok = 0;
       while (ok == 0){
13
          WorkVet[j] = WorkVet[j]+1;
14
15
          if (WorkVet[j] < Base){</pre>
16
            ok = 1;
          }
17
18
          else{
19
            WorkVet[j] = 0;
20
            j = j+1;
21
         }
22
23
       Seq[i] = sum(WorkVet * VetBase)
24
25
     return(Seq)
26 }
27
28 myprimes <-function(N){
     found = 0
29
30
     trynumber = 2
     p <- matrix()</pre>
31
32
     while (found < N){
       if (isprime(trynumber)){
33
         p <-c(p , trynumber)</pre>
34
          found = found + 1
35
       }
36
37
       trynumber = trynumber + 1
38
39
     return(p)
40 }
41
```

```
42 HaltonPaths <-function(SO, mu, sigma, T, NSteps, NRepl){
     dt = T/NSteps
43
     nudt = (mu-0.5*sigma^2)*dt
44
     sidt = sigma*sqrt(dt)
45
46
     # Use inverse transform to generate standard
        normals
47
     NormMat = matrix(0, NRepl, NSteps)
     Bases = myprimes(NSteps)
48
     RandMat <-matrix (0, NRepl, NSteps)</pre>
49
     H <- matrix()</pre>
50
     for (i in 2:(NSteps+1)){
51
52
       H = GetHalton(NRepl, Bases[i])
53
       for (j in 1:length(H)){
         RandMat[j,i-1] = invcdf(normal(),H[j])
54
       }
55
     }
56
     Increments = nudt + sidt*RandMat
57
     LogPaths = apply(cbind(log(S0)*matrix(1, NRepl,1),
58
        Increments),1,cumsum)
     LogPaths = t(LogPaths)
59
     SPaths = exp(LogPaths)
60
     SPaths[,1] = S0
61
     return(SPaths)
62
63 }
64
65 AsianHalton <-function (SO, K, r, T, sigma, NSamples, NRepl)
      ₹
66
     Payoff = matrix(0, NRepl,1)
     Path=HaltonPaths(SO,r,sigma,T,NSamples,NRepl)
67
     Payoff <-matrix (0, NSamples, 1)</pre>
68
     for(k in 1:length(Path[,1])){
69
       Payoff [k] = \max(0, \max(Path[k,2:(NSamples+1)])
70
          - K)
71
     P = mean(exp(-r*T) * matrix(Payoff))
72
73
     return(P)
74 }
75
```

```
76 set.seed(3226)

77 AsianHalton(50,50,0.1,5/12,0.4,5,1000)

78 AsianHalton(50,50,0.1,5/12,0.4,5,3000)

79 AsianHalton(50,50,0.1,5/12,0.4,5,10000)

80 AsianHalton(50,50,0.1,5/12,0.4,5,50000)

81

82 AsianHalton(50,50,0.1,2,0.4,24,1000)

83 AsianHalton(50,50,0.1,2,0.4,24,5000)

84 AsianHalton(50,50,0.1,2,0.4,24,50000)
```

 ${f R}$ code Exa 8.16 Simulating geometric Brownian motion by Halton sequences and the Brownian bridge

```
1 require(gmp)
2 require(lmom)
3 require(lestat)
4 require(matrixStats)
6 myprimes <-function(N) {
     found = 0
7
8
     trynumber = 2
     p <- matrix()</pre>
9
     while (found < N){</pre>
10
       if (isprime(trynumber)){
11
12
          p <-c(p , trynumber)</pre>
          found = found + 1
13
14
15
       trynumber = trynumber + 1
16
     return(p)
17
18 }
19
20 GetHalton <- function(HowMany, Base) {
21
     Seq = matrix(0, HowMany, 1)
     NumBits = 1+round(log(HowMany)/log(Base));
22
```

```
VetBase = Base^(-(1:NumBits));
23
     WorkVet = matrix(0,1,NumBits);
24
25
     for (i in 1:HowMany){
26
       j = 1;
27
       ok = 0;
28
       while (ok == 0){
         WorkVet[j] = WorkVet[j]+1;
29
         if (WorkVet[j] < Base){</pre>
30
           ok = 1;
31
32
         }
33
         else{
34
           WorkVet[j] = 0;
35
           j = j+1;
         }
36
       }
37
38
       Seq[i] = sum(WorkVet * VetBase)
39
40
     return(Seq)
41 }
42
43 WienerHaltonBridge <-function(T, NSteps, NRepl, Limit
      ) {
     NBisections = log2(NSteps)
44
     if (round(NBisections) != NBisections){
45
       cat ('ERROR in WienerHB: NSteps must be a power
46
          of 2', '\n')
47
       return
48
49
     # Generate standard normal samples
     NormMat = matrix(0, NRepl, NSteps)
50
     Bases = myprimes(NSteps)
51
     for (i in 2:(NSteps+1)){
52
53
       H = GetHalton(NRepl, Bases[i])
       for (j in 1:length(H)){
54
         NormMat[j,i-1] = invcdf(normal(),H[j])
55
       }
56
57
     # Initialize extreme points of paths
58
```

```
59
     WSamples = matrix(0, NRepl, NSteps+1)
60
     WSamples[,1] = 0
     WSamples[, NSteps+1] = sqrt(T)*NormMat[,1]
61
62
     # Fill paths
63
     HUse = 2
64
     TJump = T
65
     IJump = NSteps
     for (k in 1:NBisections){
66
67
       left = 1
       i = IJump/2 + 1
68
69
       right = IJump + 1
70
       for (l in 1:(2^(k-1))){
         a = 0.5*(WSamples[,left] + WSamples[,right])
71
72
         b = 0.5*sqrt(TJump)
73
         if (HUse <= Limit){</pre>
74
            WSamples[,i] = a + b*NormMat[,HUse]
75
         } else {
76
            WSamples[,i] = a + b*rnorm(NRepl)
77
78
            right = right + IJump
            left = left + IJump
79
80
            i = i + IJump
       }
81
82
       IJump = IJump/2
       TJump = TJump/2
83
84
       HUse = HUse + 1
85
       }
86
     return(WSamples)
87 }
88
   GBMHaltonBridge <-function(SO, mu, sigma, T, NSteps, NRepl
      ,Limit){
90
     if (round(log2(NSteps)) != log2(NSteps)){
       cat ('ERROR in GBMBridge: NSteps must be a power
91
          of 2', \backslash n')
92
       return
93
     }
     dt = T/NSteps
94
```

```
95
      nudt = (mu - 0.5 * sigma^2) * dt
      W = WienerHaltonBridge(T, NSteps, NRepl, Limit)
96
      Increments = nudt + sigma*t(diff(t(W)))
97
      LogPaths = apply(cbind(log(S0)*matrix(1, NRepl,1),
98
         Increments),1,cumsum)
99
      LogPaths = t(LogPaths)
100
      Paths = exp(LogPaths)
      Paths[,1] = S0
101
102
      return(Paths)
103 }
104
105 set.seed (271782)
106 \text{ NRepl} = 10000
107 T = 5
108 NSteps = 16
109 Limit = NSteps
110 \text{ SO} = 50
111 \text{ mu} = 0.1
112 \text{ sigma} = 0.4
113 Paths = GBMHaltonBridge(SO, mu, sigma, T, NSteps,
       NRepl, Limit)
114 r = mu
115 NSamples = NSteps
116 K = 55
117 Payoff <-matrix()</pre>
118 for(p in 1:length(Paths[,1])){
      Payoff[p] = max(0, mean(Paths[p,2:(NSamples+1)]) -
119
          K)
120 }
121 P = mean(exp(-r*T) * matrix(Payoff))
```

 ${f R}$ code Exa 8.17 Improving the estimate of the option Delta by Common Random Numbers

```
1 require(varbvs)
```

```
2 require(fBasics)
3 norm.interval = function(data, variance = var(data),
       conf.level = 0.95) {
     z = qnorm((1 - conf.level)/2, lower.tail = FALSE)
4
     xbar = mean(data)
     sdx = sqrt(variance/length(data))
     c(xbar - z * sdx, xbar + z * sdx)
7
8 }
9 BlsDeltaMCNaive <-function(SO,K,r,T,sigma,dS,NRepl){
     nuT = (r - 0.5*sigma^2)*T
10
     siT = sigma * sqrt(T)
11
12
     Payoff1<-matrix()</pre>
13
     Payoff2<-matrix()</pre>
     for (i in 1:NRepl){
14
       Payoff1[i] = \max(0, S0*\exp(nuT+siT*randn(1,1))-K
15
       Payoff2[i] = \max(0, (S0+dS)*\exp(nuT+siT*randn)
16
          (1,1))-K)
17
18
     SampleDiff = \exp(-r*T)*(Payoff2 - Payoff1)/dS
     parameter_estimation<-.normFit(SampleDiff)</pre>
19
     ci<-norm.interval(SampleDiff)</pre>
20
21
     return(c(parameter_estimation,ci))
22 }
23 set.seed (762567)
24 S0=50
25 K = 52
26 r = 0.05
27 T=5/12
28 \text{ sigma} = 0.4
29 NRep1=50000
30 \text{ dS} = 0.5
31 BlsDeltaMCNaive(SO,K,r,T,sigma,dS,NRepl)
```

R code Exa 8.18 Estimating the option Delta by a pathwise estimator

```
1 require(varbvs)
2 require(fBasics)
3 norm.interval = function(data, variance = var(data),
       conf.level = 0.95) {
     z = qnorm((1 - conf.level)/2, lower.tail = FALSE)
     xbar = mean(data)
     sdx = sqrt(variance/length(data))
     c(xbar - z * sdx, xbar + z * sdx)
7
8 }
9
10 BlsDeltaMCPath <-function(SO,K,r,T,sigma,NRepl){</pre>
     nuT = (r - 0.5*sigma^2)*T
11
12
     siT = sigma * sqrt(T)
     VLogn<-matrix()</pre>
13
14
     for (i in 1:NRepl){
       VLogn[i] = exp(nuT+siT*randn(1,1))
15
16
     SampleDelta = exp(-r*T) * VLogn * (S0*VLogn > K)
17
     parameter_estimation <-.normFit(SampleDelta)</pre>
18
19
     ci<-norm.interval(SampleDelta)</pre>
20
     return(c(parameter_estimation,ci))
21 }
22
23 set.seed (3725678)
24 S0 = 50
25 K = 52
26 r = 0.05
27 T=5/12
28 \text{ sigma} = 0.4
29 NRepl=50000
30 BlsDeltaMCPath(SO,K,r,T,sigma,NRepl)
```

Chapter 9

Option Pricing by Finite Difference Methods

R code Exa 9.3 price a European vanilla put by a straightforward explicit scheme

```
1 require(pracma)
3 EuPutExpl <-function(S0,K,r,T,sigma,Smax,dS,dt){</pre>
     # set up grid and adjust increments if necessary
4
     M = round(Smax/dS)
     dS = Smax/M
     N = round(T/dt)
    dt = T/N
     matval = matrix(0, M+1, N+1)
10
     vetS = seq(0,Smax,length=M+1)
     veti = 0:M
11
12
    vetj = 0:N
13
    # set up boundary conditions
14
    for (k in 1:(M+1)){
15
       matval[k,N+1] = max(K-vetS[k],0)
16
     matval[1,] = K*exp(-r*dt*(N-vetj))
17
18
     matval[M+1,] = 0
```

```
# set up coefficients
19
     a = 0.5*dt*(sigma^2*veti - r)*veti
20
21
     b = 1 - dt*(sigma^2*veti^2 + r)
     c = 0.5*dt*(sigma^2*veti + r)*veti
22
23
    # solve backward in time
     for (j in N:1){
24
       for (i in 2:M){
25
         matval[i,j] = a[i]*matval[i-1,j+1] + b[i]*
26
            matval[i,j+1]+ c[i]*matval[i+1,j+1]
       }
27
28
29
    # return price, possibly by linear interpolation
        outside the grid
     price = interp1(vetS, matval[,1], S0)
30
     return(price)
31
32 }
33 EuPutExpl (50,50,0.1,5/12,0.4,100,2,5/1200)
34 EuPutExpl (50,50,0.1,5/12,0.3,100,2,5/1200)
35 EuPutExpl (50,50,0.1,5/12,0.3,100,1.5,5/1200)
36 EuPutExpl (50,50,0.1,5/12,0.3,100,1,5/1200)
```

R code Exa 9.4 price a vanilla European option by a fully implicit method

```
1 require(pracma)
3 EuPutImpl <- function(SO,K,r,T,sigma,Smax,dS,dt){</pre>
     # set up grid and adjust increments if necessary
4
5
     M = round(Smax/dS)
6
     dS = Smax/M
     N = round(T/dt)
8
     dt = T/N
     matval = matrix(0, M+1, N+1)
     vetS = seq(0,Smax,length=M+1)
10
11
     veti = 0:M
12
     vetj = 0:N
```

```
13
     # set up boundary conditions
14
     for (k in 1:(M+1)){
       matval[k,N+1] = max(K-vetS[k],0)
15
16
17
     matval[1,] = K*exp(-r*dt*(N-vetj))
18
     matval[M+1,] = 0
19
     # set up the tridiagonal coefficients matrix
     a = 0.5*(r*dt*veti-sigma^2*dt*(veti^2))
20
21
     b = 1 + sigma^2 * dt * (veti^2) + r * dt
22
     c = -0.5*(r*dt*veti+sigma^2*dt*(veti^2))
23
     zero <-matrix (0,1,M-1)
24
     coeff = (diag(c(0,a[3:M],0)))[1:M-1,2:M] + diag(b)
        [2:M]) + (rbind(diag(c[2:M-1]),zero))[2:M,1:(M
        -1)]
     L = lu(coeff)$L
25
     U = lu(coeff) \$ U
26
     # solve the sequence of linear systems
27
     aux = matrix(0, M-1, 1)
28
     for (j in N:1){
29
       aux[1] = -a[2] * matval[1,j]
30
       # other term from BC is zero
31
32
       matval[2:M,j] = solve(U,(solve(L,(matval[2:M,j
          +1] + aux))))
33
     # return price, possibly by linear interpolation
34
        outside the grid
     price = interp1(vetS, matval[,1], S0)
35
36
     return(price)
37 }
38 EuPutImpl (50,50,0.1,5/12,0.4,100,0.5,5/2400)
```

 ${f R}$ code ${f Exa}$ 9.5 price a down and out put option by the Crank Nicolson method

```
1 require(pracma)
```

```
2
3 DOPutCK<-function(SO,K,r,T,sigma,Sb,Smax,dS,dt){</pre>
     # set up grid and adjust increments if necessary
     M = round((Smax - Sb)/dS)
5
6
     dS = (Smax - Sb)/M
7
     N = round(T/dt)
8
     dt = T/N
     matval = matrix(0, M+1, N+1)
9
10
     vetS = seq(Sb,Smax,length = M+1)
     veti = vetS / dS
11
12
     vetj = 0:N
13
     # set up boundary conditions
14
     for (k in 1:(M+1)){
       matval[k,N+1] = max(K-vetS[k],0)
15
16
     }
17
     matval[1,] = 0
     matval[M+1,] = 0
18
19
     # set up the coefficients matrix
20
     alpha = 0.25*dt*(sigma^2*(veti^2) - r*veti)
     beta = -dt*0.5*(sigma^2*(veti^2) + r)
21
22
     gamma = 0.25*dt*(sigma^2*(veti^2) + r*veti)
23
     zero<-matrix(0,1,M-1)
     M1 = -(diag(c(0, alpha[3:M], 0)))[1:M-1, 2:M] + diag
24
        (1-beta[2:M]) - (rbind(diag(gamma[2:M-1]),zero)
        )[2:M,1:(M-1)]
     L = lu(M1) L
25
26
     U = lu(M1)\$U
     M2 = (diag(c(0, alpha[3:M], 0)))[1:M-1, 2:M] + diag
27
        (1+beta[2:M]) + (rbind(diag(gamma[2:M-1]),zero)
        )[2:M,1:(M-1)]
     # solve the sequence of linear systems
28
     for (j in N:1){
29
30
       matval[2:M,j] = solve(U, solve(L, (M2%*%matval[2:M
          , j+1])))
31
     # return price, possibly by linear interpolation
32
        outside the grid
33
     price = interp1(vetS, matval[,1], S0)
```

Chapter 10

Dynamic Programming

 ${f R}$ code Exa 10.4 Simple asset allocation problem under uncertainty Monte Carlo sampling

```
1 require(varbvs)
2 require(pracma)
3 require(zeallot)
4 OptFolioMC <-function(WO,SO,mu,sigma,r,T,NScen,utilf)
      {
     muT = (mu - 0.5*sigma^2)*T
     sigmaT = sigma*sqrt(T)
     R = exp(r*T)
8
     NormSamples = muT + sigmaT*randn(NScen,1)
9
     ExcessRets = exp(NormSamples) - R
10
     MExpectedUtility <- function(x){</pre>
       -mean(utilf(W0*((x*ExcessRets) + R)))
11
12
     share = fminbnd(MExpectedUtility, 0, 1)
13
14
     return(share)
15 }
16 set.seed(294)
17 share = OptFolioMC(1000,50,0.1,0.4,0.05,1,10000,log)
18 share $xmin
19
```

```
20
21 set.seed(2947)
22 share = OptFolioMC(1000,50,0.1,0.4,0.05,1,5000000,
      log)
23 share $xmin
24
25 OptFolioGauss <-function(WO,SO,mu,sigma,r,T,NScen,
      utilf){
     muT = (mu - 0.5*sigma^2)*T
26
27
     sigmaT = sigma*sqrt(T)
     R = \exp(r*T)
28
29
     print(GaussHermite(muT, sigmaT^2, NScen))
30
     c(x,w) %<-% GaussHermite(muT, sigmaT^2, NScen)</pre>
     ExcessRets = exp(x) - R
31
     MExpectedUtility <-function(x){</pre>
32
       - Re(dot(Re(w), utilf(W0*((Re(x)*ExcessRets) +
33
          R))))
34
     share = fminbnd(MExpectedUtility, 0, 1)
35
36 }
37
38
39 GaussHermite <-function (mu, sigma2, N) {
     HPoly1 = c(1/pi^0.25)
40
     HPoly2 = c(sqrt(2) / pi^0.25, 0)
41
42
     for (j in 1:(N-1)){
43
       HPoly3 = c(sqrt(2/(j+1)) * HPoly2 , 0) - c(0, 0,
           sqrt(j/(j+1))*HPoly1)
       HPoly1 = HPoly2
44
       HPoly2 = HPoly3
45
     }
46
47
     x1 = polyroot(HPoly3)
48
     w1 = matrix(0,N,1)
49
     for (i in 1:N){
       w1[i] = 1/(N)/(polyval(HPoly1, x1[i]))^2
50
51
     x = sort(x1*sqrt(2*sigma2)+mu)
52
     index = order(x1*sqrt(2*sigma2)+mu)
53
```