

Question 3)

Code:

```
1. # importing the necessary packages
2. import numpy as np
3. from numpy import sqrt, exp, log, mean
4. from scipy.stats import norm
5. from scipy import optimize
6.
7. #####
8.
9. # increment step method for Brownian Motion
10. def SimBMStep(T, N):
11.     # initialize W brownian motion array
12.     W = np.zeros(int(N))
13.     W = np.append(W, 0)    # initial 0 value
14.
15.     # loop
16.     num = 0
17.     while num < N:
18.         W[num + 1] = W[num] + sqrt(T/N)*np.random.standard_normal()
19.         num += 1
20.
21.     return W
22.
23. # initial vars
24. s = 143.    # retrieved from APPL stock
25. sigma_init = 3.0    # initial guess for sigma
26.
27. # number retrieved from 30yr treasury bond yield curve rate
28. r = 0.0320
29.
30. # day form
31. T = 36/365.
32. runs = 1000
33.
34. # this is all XDATA
35. # these are the K strike CALL options that have trading volume of more than 10
36. CK = np.array([50, 110, 120, 130, 135, 140, 145, 150, 155, 160, 165, 170, 175, 180])
37.
38. #CK_thetaPrices = np.zeros(0)
39. CK_actualPrices = np.array([mean([86.40,87.10]),
40.                             mean([33.50,34.25]),
41.                             mean([24.15,24.45]),
42.                             mean([14.50,14.65]),
43.                             mean([10.15,10.25]),
44.                             mean([6.50,6.55]),
45.                             mean([3.75,3.80]),
46.                             mean([1.89,1.89]),
47.                             mean([0.89,0.91]),
48.                             mean([0.42,0.44]),
49.                             mean([0.21,0.22]),
50.                             mean([0.10,0.11]),
51.                             mean([0.05,0.06]),
52.                             mean([0.02,0.03])])
53.
54.
55. print("K strike values for Call options (these have volume traded > 10):")
56. print(CK)
57. print("Call option actual prices (ordered with their respective K's): ")
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```
58. print(CK_actualPrices)
59.
60. # payoff function for European Call option
61. def payoffEC(ST, K):
62.     return max(ST - K, 0)
63.
64. # big MAIN FUNCTION that has all parameters for optimization
65. # and outputs the estimated model prices
66. # xdata is the K value
67. def PricingUsingModelEC(K, sigma_init):
68.     num = 0
69.     totalPayoffs = np.zeros_like(CK)
70.     # monte carlo simulation loop
71.     while num < runs:
72.         payoffs = np.zeros(0)
73.         W1 = SimBMStep(T, 500.)
74.         temp = 0
75.         St = np.zeros(0)
76.         St = np.append(St, s)
77.         # St simulation loop
78.         while temp < 500:
79.             St = np.append(St, St[temp]
80.                             + r*St[temp]*(T/500.)
81.                             + sigma_init*St[temp]*(W1[temp+1] - W1[temp]))
82.             temp += 1
83.         # retrieving the terminal ST
84.         ST = St[St.size - 1]
85.         payoffs = ST - K
86.         # this makes every payoff value >= 0
87.         payoffs = [0 if i<0 else i for i in payoffs]
88.         totalPayoffs = np.sum([payoffs, totalPayoffs], axis = 0)
89.         num += 1
90.     AveragePayoffs = [i/runs for i in totalPayoffs]
91.     EstimatedPrices = [exp(-r*T)*i for i in AveragePayoffs]
92.     return EstimatedPrices
93.
94. # regular BS pricing formula
95. def PricingUsingClosedForm(K, sigma_init):
96.     d1 = (log(s/K) + (r + (sigma_init**2)/2)*T) / (sigma_init * sqrt(T))
97.     d2 = d1 - sigma_init*sqrt(T)
98.     # black scholes formula price calculation
99.     PriceBS = s*norm.cdf(d1) - K*exp(-r*T)*norm.cdf(d2)
100.    return PriceBS
101.
102.
103.    # finally, we do curve_fit optimization, Monte Carlo integration version
104.    popt, pcov = optimize.curve_fit(PricingUsingModelEC, CK, CK_actualPrices)
105.    print("MC: If initial sigma guess = " + str(sigma_init) + ", then optimal sigma
    = " + str(round(popt,2)))
106.
107.    # BS formula version
108.    popt, pcov = optimize.curve_fit(PricingUsingClosedForm, CK, CK_actualPrices)
109.    print("BS: If initial sigma guess = " + str(sigma_init) + ", then optimal sigma
    = " + str(round(popt,2)))
110.
```

a)

Output:

K strike values for Call options (these have volume traded > 10):

[50 110 120 130 135 140 145 150 155 160 165 170 175 180]

Call option actual prices (ordered with their respective K's):

[8.67500000e+01 3.38750000e+01 2.43000000e+01 1.45750000e+01
1.02000000e+01 6.52500000e+00 3.77500000e+00 1.89000000e+00
9.00000000e-01 4.30000000e-01 2.15000000e-01 1.05000000e-01
5.50000000e-02 2.50000000e-02]

MC: If initial sigma guess = 0.2, then optimal sigma = 1.0

MC: If initial sigma guess = 0.3, then optimal sigma = 1.0

MC: If initial sigma guess = 0.02, then optimal sigma = 1.0

MC: If initial sigma guess = 3.0, then optimal sigma = 1.0

b)

Output:

BS: If initial sigma guess = 0.2, then optimal sigma = 0.26

BS: If initial sigma guess = 0.3, then optimal sigma = 0.26

BS: If initial sigma guess = 0.02, then optimal sigma = 0.26

BS: If initial sigma guess = 3.0, then optimal sigma = 0.26

c)

As clearly seen, the Monte Carlo model calibration for sigma resulted in 1.0 while the closed form Black Scholes formula model calibration for sigma resulted in 0.26.

Naturally 0.26 seems like the reasonable result.

I believe because the Monte Carlo routine uses a large size of data for the simulation process, this creates discrepancies. In addition, curve_fit optimization method uses the Levenberg-Marquardt algorithm, which expects smooth and "well-behaved" statistical world. However the Monte Carlo simulation process is not a simple world, therefore it is difficult for the curve_fit optimization method to work properly with Monte Carlo integration.