## Stochastic Simulation (MIE1613H) - Homework 1 (Solutions)

Due: Jan 29, 2019

**Problem 1.** Assume that X is exponentially distributed with rate  $\lambda = 0.2$ . We are intreated in computing  $E[(X-3)^+]$ . (Note:  $a^+ = \text{Max}(a,0)$ , i.e, if a < 0 then  $a^+ = 0$  and if  $a \ge 0$  then  $a^+ = a$ .)

- (a) Compute the expected value exactly.
- (5 points) Recalling that the pdf of an exponential random variable is  $\lambda e^{-\lambda x}$  and using the defenition of the expected value of a function of a continuous random variable we have,

$$E[(X-3)^+] = \int_0^{+\infty} (x-3)^+ \lambda e^{-\lambda x} dx$$
$$= \int_3^{+\infty} (x-3)\lambda e^{-\lambda x} dx.$$

Define u = (x - 3). The integral can be written as

$$E[(X-3)^+] = \int_0^{+\infty} u\lambda e^{-\lambda(u+3)} du = e^{-3\lambda} \int_0^{+\infty} u\lambda e^{-\lambda u} du$$

Note that  $\int_0^{+\infty} u\lambda e^{-\lambda u} du$  is the expected value of an exponential r.v. with rate  $\lambda$  and is hence equal to  $1/\lambda$ . It follows that

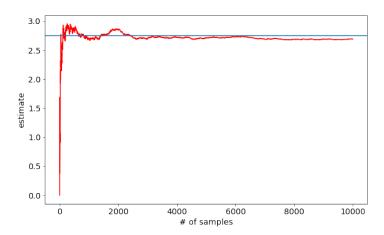
$$E[(X-3)^+] = e^{-3\lambda}(1/\lambda) = e^{-0.6}(5) \approx 2.744.$$

- (b) Estimate the expected value using Monte Carlo simulation and provide a 95% confidence interval for your estimate. **Note**: You can generate a random sample of an exponentially distributed random variable with rate  $\lambda$  in Numpy using np.random.exponential(1/ $\lambda$ ).
- (10 points) To estimate the expected value we generate n = 10,000 iid samples of the random variable  $(X 3)^+$  and compute the sample average. The estimate is 2.69 and the 95% CI is given by [2.60, 2.78] which includes the exact value.
- (c) Create a plot that demonstrates the convergence of the Monte Carlo estimate to the exact value as the number of samples increases.
- (5 points) See the source code and the output below.

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 import scipy.stats as stats
4 np.random.seed(1)
5
6 def mean_confidence_interval_95(data):
7 a = 1.0*np.array(data)
```

```
8
        n = len(a)
9
        m, se = np.mean(a), stats.sem(a)
10
        h = 1.96 * se
11
        return m, m-h, m+h
12
13
   samples = []
   estimates = []
14
15
    for n in range (0,10000):
16
        \# generate a sample of the random variable and
17
        # append to the list
        samples.append (\max(\text{np.random.exponential}(1/0.2)-3.0))
18
19
        estimates.append(np.mean(samples))
    print ("The_estimate_and_95%_CI:",
20
21
          mean confidence interval 95 (samples))
22
23
   plt.plot(estimates, 'r')
   plt.xlabel('#_of_samples')
24
   plt.ylabel('estimate')
25
   plt. axhline (y=2.744)
26
27
   plt.rcParams['figure.figsize'] = (10, 6)
   plt.rcParams.update({ 'font.size': 14})
29
   plt.show()
```

The estimate and 95% CI:, (2.690673712038912, 2.605194278819423, 2.776153145258401)



**Problem 2**. In the TTF example from the first class we simulated the system until the time of first failure. Modify the simulation model to simulate the system for a given number of days denoted by T. Assume that all other inputs and assumptions are the same as in the original example.

(a) What is the average number of functional components until time T = 1000 based on one replication of the simulation?

(20 points) The logic is modified as follows. When the system fails, i.e., S = 0, one repair is still pending. Therefore, we do not reschdule another repair but set the NextFailure to  $\infty$ . In addition, if S = 1 after the completion of a repair, we need to schedule the repair of the other component, and the failure of the component that just started working. Simulating one sample path of the process

S(t) for T=1000 time units we have

$$\frac{1}{1000} \int_0^{1000} S(t)dt = 1.2645.$$

(b) What is the average number of functional components until time T=2000 based on one replication of the simulation? Compare the results from part (a) and (b) and summerize your observation in one sentence.

(10 points) For T = 2000 we get

$$\frac{1}{2000} \int_0^{2000} S(t)dt = 1.2685.$$

We observe that the results of part (a) and (b) are approximately the same suggesting that the time-average is converging to some constant  $\theta$ , which is the long-run average number of functioning components:

$$\theta = \lim_{T \to \infty} \frac{1}{T} \int_0^T S(t) dt.$$

```
1
   import numpy as np
2
3
   def EndSim ():
4
       global Slast
5
        global Tlast
6
        global Area
7
8
        Area = Area + (clock - Tlast)* Slast
9
       Tlast = clock
       Slast = S
10
11
   def Failure ():
12
       global S
13
14
        global Slast
15
       global Tlast
16
        global Area
17
       global NextFailure
18
       global NextRepair
19
       S = S - 1
20
       if S == 0:
21
22
            NextFailure = float('inf')
23
            # repair already in progress
24
        if S == 1:
25
            NextRepair = clock + 2.5
26
            NextFailure = clock + np.ceil(6*np.random.random())
27
        # Update the area under the sample path and the time and state at the
           last event
28
        Area = Area + (clock - Tlast)* Slast
29
       Tlast = clock
30
       Slast = S
```

```
31
32 def Repair():
33
       global S
        global Slast
34
35
       global Tlast
36
       global Area
37
       global NextFailure
38
       global NextRepair
39
40
       S = S + 1
41
       if S == 1:
42
            NextRepair = clock + 2.5
43
            NextFailure = clock + np.ceil(6*np.random.random())
        else: \#S = = 2
44
45
            NextRepair = float('inf')
46
        Area = Area + Slast * (clock - Tlast)
47
        Slast = S
48
        Tlast = clock
49
50 \text{ def Timer()}:
51
       global clock
       global NextRepair
52
53
       global NextFailure
54
55
       if NextEndSim < NextFailure and NextEndSim < NextRepair:</pre>
            result = "EndSim"
56
57
            clock = NextEndSim
58
59
        elif NextFailure < NextRepair:</pre>
60
            result = "Failure"
61
            clock = NextFailure
62
63
       else:
            result = "Repair"
64
65
            clock = NextRepair
66
       return result
67
68
69 # fix random number seed
70 np.random.seed(1)
71
72 \text{ clock} = 0
73 \, \text{S} = 2
74 # initialize the time of events
75 NextRepair = float('inf')
76 NextFailure = np.ceil(6*np.random.random())
77 NextEndSim = 2000
78 # Define variables to keep the area under the sample path
79 # and the time and state of the last event
80 \text{ Area} = 0.0
81 Tlast = 0
82 Slast = 2
83 NextEvent = Timer()
84
```

```
85
   while NextEvent!="EndSim":
86
        NextEvent = Timer()
87
        if NextEvent == "Repair":
88
            Repair()
89
        elif NextEvent == "Failure":
90
            Failure()
91
        else:
92
            EndSim()
93
94
   print('Average_#_of_func._comp._till_failure:', Area/clock)
```

Average # of func. comp. till failure: 1.2685

**Problem** 3. Modify the TTF simulation assuming that there are three components, one active and two spares, but still only one can be repaired at a time. Repair time is 3.5 days. Run your simulation for 1000 replications and report a 95% confidence interval for the expected time to failure of the system.

(20 points) With three components the logic is modified as follows. When a failure happens, we have S=2 or S=1. If S=2, then a new component starts working and a new repair begins. Therefore, we need to schedule both the next failure and repair events. If S=1, then a repair is already in progress and therefore we only schedule the next failure for the component that just started working. When a repair is completed we have S=3 or S=2. If S=3, then a failure is still pending and all components are functioning. Therefore we only need to set the next failure time to  $\infty$ . If S=2, again a failure is still pending but a new repair starts which we need to schedule.

Based on n = 1000 replications the 95% CI for the expected average number of functioning components until failure is [37.05, 41.43].

```
import numpy as np
   import scipy stats as stats
3
   def mean confidence interval 95 (data):
4
5
       a = 1.0*np.array(data)
6
       n = len(a)
7
       m, se = np.mean(a), stats.sem(a)
8
       h = 1.96 * se
       9
10
11
   def Failure ():
12
       global S
13
       global Slast
14
       global Tlast
15
        global Area
16
       global NextFailure
17
       global NextRepair
18
       S = S - 1
19
       if S == 2:
20
21
            NextRepair = clock + 3.5
22
            NextFailure = clock + np.ceil(6*np.random.random())
23
       else: \# S==1
24
           # one repair is already in progress
```

```
25
            NextFailure = clock + np.ceil(6*np.random.random())
26
       # Update the area under the sample path and the time and state at the last
27
        Area = Area + (clock - Tlast)* Slast
28
        Tlast = clock
        Slast = S
29
30
31
   def Repair():
32
        global S
33
        global Slast
34
        global Tlast
        global Area
35
        global NextFailure
36
37
        global NextRepair
38
39
        S = S + 1
        if S == 3:
40
41
            # a failure is still pending so no need to schedule a new one
            # all components functioning
42
43
            NextRepair = float('inf')
        \mathtt{else}: \ \# \ S == \ 2
44
            # a new repair starts; one failure pending
45
            NextRepair = clock + 3.5
46
        Area = Area + Slast * (clock - Tlast)
47
        Slast = S
48
49
        Tlast = clock
50
51
   def Timer():
        global clock
52
        global NextRepair
53
54
        global NextFailure
55
        if NextFailure < NextRepair:
56
            result = "Failure"
57
            clock = NextFailure
58
59
60
        else:
            result = "Repair"
61
            clock = NextRepair
62
63
        return result
64
65
66 # Set number of replications
67 N = 1000
68 # Define lists to keep samples of the outputs across replications
   TTF_list = []
70 Ave list = []
71
72 # fix random number seed
73 \operatorname{np.random.seed}(1)
74
75 # Replication loop
76 for reps in range (0,N):
       \# start with 2 functioning components at time 0
77
```

```
clock = 0
78
         S = 3
79
80
         \# initialize the time of events
81
         NextRepair = float ('inf')
82
         NextFailure = np.ceil(6*np.random.random())
83
         \# Define variables to keep the area under the sample path
         # and the time and state of the last event
84
85
         Area = 0.0
         Tlast = 0
86
87
         Slast = 2
88
         while S > 0: # While system is functional
89
             NextEvent = Timer()
90
91
             if NextEvent == "Repair":
92
                 Repair()
93
94
             else:
                 Failure()
95
96
97
         \# add samples to the lists
         TTF list.append(clock)
98
99
         Ave list.append(Area/clock)
100
101
    print ('95%_CI_for_the_expected_time_to_failure:', mean confidence interval 95(
        TTF list))
```

95% CI for the expected time to failure:, (39.239, 37.0480606471163, 41.42993935288369))

**Problem** 4. The standard error of an estimator is defined as the standard deviation of that estimator. In class we introduced the sample mean  $\bar{X}_n = (1/n) \sum_{i=1}^n X_i$  as an estimator of E[X] where  $X_i$ 's are iid samples of the random variable X. What is the standard error of the estimator  $\bar{X}_n$ ? Assume that the standard deviation of X is  $\sigma$ .

(15 points) The variance of the estimator is given by

$$Var(\bar{X}_n) = Var(\frac{1}{n}\sum_{i=1}^{n}X_i) = \frac{1}{n^2}nVar(X_1) = \frac{1}{n}Var(X_1).$$

Therefore, the standard deviation is

$$\sqrt{Var(\bar{X}_n)} = \sqrt{\frac{1}{n}Var(X_1)} = \frac{\sigma}{\sqrt{n}}.$$

**Problem 5.** If you buy a lottery ticket in 50 lotteries, in each of which your chance of winning a prize is 1/200, what is the (approximate) probability that you will win a prize (a) at least once, (b) exactly once, (c) at least twice?

(15 points) The number of lotteries in which you win a prize N has a Binomail distribution with parameters n = 50 and p = 1/200. Since, n is large and p is small we can approximate the Binomial distribution using a Poisson distribution with mean np = 1/4. Therefore,

$$P(N=n) \approx \frac{e^{-(1/4)}(1/4)^n}{n!}.$$

- (a)  $P(N \ge 1) = 1 P(N = 0) \approx 1 e^{-1/4} \approx 0.2212$ .
- (b)  $P(N=1) \approx (1/4)e^{-1/4} \approx 0.1947$ .
- (c)  $P(N \ge 2) = 1 P(N = 0) P(N = 1) = 1 e^{-1/4} (1/4)e^{-1/4} \approx 0.0265$ .