

## STATS 255 Assignment 4

1.

- a. A warmup period is a set of cycles used to let the system stabilize before information begins to be recorded. We use a warmup period because stochastic processes approach a steady state probability distribution after many cycles but initially can go all over the place. If we did not use a warm-up period, then these unpredictable cycles would damage the reliability of our average stock estimates.

b. Scenario 1:

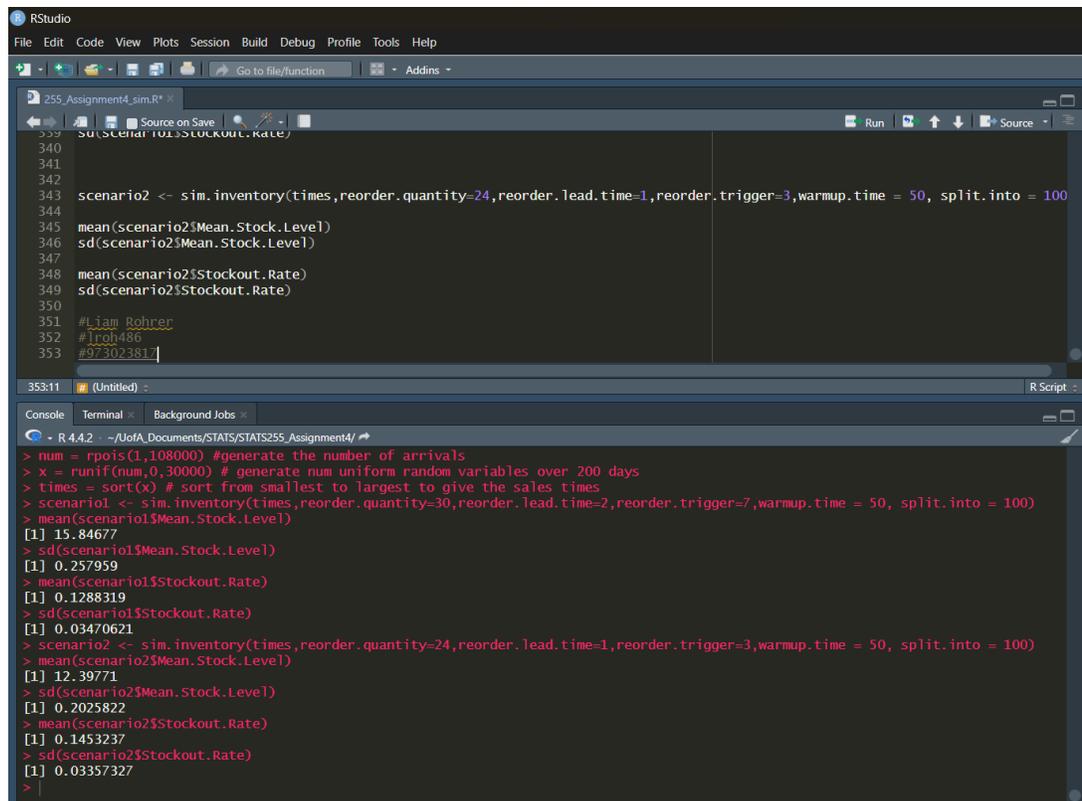
Stock mean CI =  $15.8467 \pm 1.96(0.2579/\sqrt{100}) \rightarrow (15.796, 15.897)$

Stockout rate CI =  $0.1288 \pm 1.96(0.0347/\sqrt{100}) \rightarrow (0.1220, 0.1356)$

Scenario 2:

Stock mean CI =  $12.39771 \pm 1.96(0.2025/\sqrt{100}) \rightarrow (12.358, 12.437)$

Stockout rate CI =  $0.1453 \pm 1.96(0.0335/\sqrt{100}) \rightarrow (0.1387, 0.1519)$



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RStudio
File Edit Code View Plots Session Build Debug Profile Tools Help
255_Assignment4_sim.R
339 su(scenario1$STOCKOUT.Rate)
340
341
342
343 scenario2 <- sim.inventory(times,reorder.quantity=24,reorder.lead.time=1,reorder.trigger=3,warmup.time = 50, split.into = 100)
344
345 mean(scenario2$Mean.Stock.Level)
346 sd(scenario2$Mean.Stock.Level)
347
348 mean(scenario2$Stockout.Rate)
349 sd(scenario2$Stockout.Rate)
350
351 #Liam Rohrer
352 #lroh486
353 #973023817

353:11 (Untitled) R Script
Console Terminal Background Jobs
R 4.4.2 ~/JofA Documents/STATS/STATS255_Assignment4/
> num = rpois(1,108000) #generate the number of arrivals
> x = runif(num,0,300000) # generate num uniform random variables over 200 days
> times = sort(x) # sort from smallest to largest to give the sales times
> scenario1 <- sim.inventory(times,reorder.quantity=30,reorder.lead.time=2,reorder.trigger=7,warmup.time = 50, split.into = 100)
> mean(scenario1$Mean.Stock.Level)
[1] 15.84677
> sd(scenario1$Mean.Stock.Level)
[1] 0.257959
> mean(scenario1$Stockout.Rate)
[1] 0.1288319
> sd(scenario1$Stockout.Rate)
[1] 0.03470621
> scenario2 <- sim.inventory(times,reorder.quantity=24,reorder.lead.time=1,reorder.trigger=3,warmup.time = 50, split.into = 100)
> mean(scenario2$Mean.Stock.Level)
[1] 12.39771
> sd(scenario2$Mean.Stock.Level)
[1] 0.2025822
> mean(scenario2$Stockout.Rate)
[1] 0.1453237
> sd(scenario2$Stockout.Rate)
[1] 0.03357327
>
```

- c. Option two does not do this. We know this because the lower limit of our 95% confidence interval is 0.1387, well above the 0.05 mark.
- d. Only considering mean stock levels, we do have sufficient evidence to conclude that option two is better than option one. We know this because the mean stock level is lower and the confidence intervals do not overlap.

2.

a.

- i. A Poisson process might be a good model because the arrivals are random and independent, and this is essentially the kind of situation that Poisson models are made for. The area in which it might not accurately represent reality is in the use of the average arrival rate as stationary throughout the day. There are likely to be periods that tend to be more or less busy which this will not take into account.
- ii. This queue is stable because our one server can process up to 40 people in an hour, and our arrival rate is only 24 per hour, meaning the queue will not build endlessly.
- iii. The expected time before the next customer arrives is given by  $E[X \sim \text{exp}(24)]$  which evaluates to **1/24 hours**.
- iv. Expected number of arrivals in 1/6 hours =  $E[X \sim \text{poisson}(24)]/6 \rightarrow$  **4 arrivals**
- v.  $P(X=0) = (4^0 e^{-4})/0! \rightarrow$  **0.01831**
- vi.  $P(X=3) = (4^3 e^{-4})/3! \rightarrow 0.1953$        $0.01831 * 0.1953 =$  **0.00358**

b. ( $\rho = 24/40 \rightarrow 0.6$ )

- i.  $L = 24/(40-24) \rightarrow$  **1.5 people**     $W = 1/(40-24) \rightarrow$  **0.0625 hours**
- ii.  $L_q = 0.6^2/(1-0.6) \rightarrow$  **0.9 people**       $W_q = 24/(40(40-24)) \rightarrow$  **0.0375 hours**
- iii.  $p_0 = (1-0.6)0.6^0 \rightarrow$  **0.4**       $p_1 = (1-0.6)0.6^1 \rightarrow$  **0.24**       $p_2 = (1-0.6)0.6^2 \rightarrow$  **0.144**
- iv.  $p_{x>=3} = 1 - (p_0 + p_1 + p_2) = 1 - (0.4 + 0.24 + 0.144) =$  **0.216**

c.

- i. We can combine arrival rates because both follow a Poisson distribution.
- ii. **QUEUEING SIMULATION**

**Customer arrival process:**

Inter-arrival time distn:	exponential, rate 29.600000000000005
Routing upon arrival to:	Q1

**Queueing:**

	Capacity	No. servers	Service time distn.	Onward routing to
Q1	unlimited	1	exponential, rate 40	exit

**Simulation details:**

Number of runs:	100
Run duration (warmup):	20
Run duration (data collection):	220
Random seed:	9730

- iii.  $L_q = 2.1108 \pm 1.96(0.2615/\sqrt{100}) \rightarrow$  **(2.0595, 2.1621)**  
 $W_q = 0.071 \pm 1.96(0.008/\sqrt{100}) \rightarrow$  **(0.06943, 0.0726)**
- iv.  $p_{x>=3} = 1 - (p_0 + p_1 + p_2) \rightarrow 1 - (0.2604 + 0.1927 + 0.1427) =$  **0.4042**
- v. We see a considerable increase in both the number of customers and time in the system. The average time customers are waiting in the queue is still well within the 5 minute threshold set by the manager, but the average queue length has increased beyond 2 people. According to the manager's guidelines, I would suggest hiring part time help during this period.