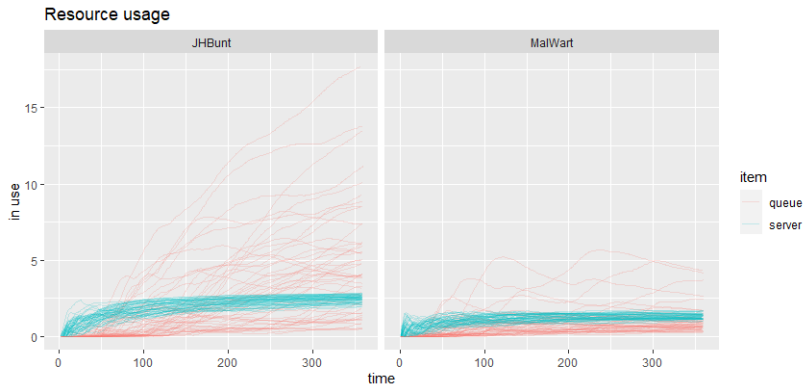


Monitoring and Visualising the Simulations



Outline

- 1 Multiple Replications and Fetch the Monitor Data
- 2 Monitor the Resources, Arrivals and Attributes Data
- 3 Visualise the Resources Data
- 4 Utilise the Arrivals Data to Compute the Mean Waiting Time
- 5 Summary

Learning Objectives

In this video, we will

- Run the simulations multiple times.
- Monitor and visualise the results of the simulations: arrivals, attributes and resources.

Multiple Replications

- The simulation model simulates the STEM event for 360 minutes.
- We will run the simulation model 50 times.

```
set.seed(2909)
mm2.envs <- replicate(50,
  simmer("mixer") %>%
    add_resource("MalWart", capacity = 2) %>%
    add_resource("JHBunt", capacity = 3) %>%
    add_generator("Student", student,
      function() rexp(1, 1/2), mon = 2) %>%
    run(until = 360) %>% wrap())
```

...

357.646: Student172: Here I am

358.139: Student172: I have affixed my name tag!

358.657: Student167: I shall join the queue and talk to a MalWart recruiter

359.777: Student173: Here I am

Target Outcomes

- Recall that we were interested to study three particular performance measures.
 - ▶ The utilisation of the recruiters at each company booth.
 - ▶ The number of students waiting in line at each booth.
 - ▶ The mean wait time of students during the mixer.
- To extract the relevant monitor data that we need, we run the following three lines of code on the 50 simulation environments that we have generated.

```
mon_resources <- get_mon_resources(mm2.envs)
mon_arrivals <- get_mon_arrivals(mm2.envs)
mon_attributes <- get_mon_attributes(mm2.envs)
```

Monitor the Resources Data

- Let's begin by inspecting the rows in the 'mon_resources' table.

```
knitr::kable(head(mon_resources))
```

resource	time	server	queue	capacity	system	limit	replication
MalWart	5.156790	1	0	2	1	Inf	1
MalWart	5.436570	0	0	2	0	Inf	1
JHBunt	5.436570	1	0	3	1	Inf	1
MalWart	9.106437	1	0	2	1	Inf	1
MalWart	11.495920	0	0	2	0	Inf	1
JHBunt	11.495920	2	0	3	2	Inf	1

- We can conclude that a student talked to a Malwart recruiter at 5.16 minutes, and he left the counter at 5.44 minutes.

Monitor the Arrivals Data

- Now, let us inspect the rows in the 'mon_arrivals' table.

```
knitr::kable(head(mon_arrivals))
```

name	start_time	end_time	activity_time	finished	replication
:-----	-----:	-----:	-----:	:-----	-----:
Student3	8.642642	12.76900	4.126363	TRUE	1
Student1	4.484858	25.34722	20.862361	TRUE	1
Student8	20.554220	25.36857	4.814350	TRUE	1
Student2	4.874769	28.54394	23.669175	TRUE	1
Student11	27.536154	34.41472	6.878562	TRUE	1
Student0	2.255781	38.55244	33.108475	TRUE	1

- For example, the student 3 arrived at 8.64 minutes, and left at 12.77 minutes. In total, he spent 4.13 minutes in the activities.

Monitor the Arrivals Data

cont'd

- To know the breakdown activity time per resource, we can use the following code.

```
mon_arrivals_sub <- get_mon_arrivals(mm2.envs, per_resource = TRUE)
knitr::kable(head(mon_arrivals_sub))
```

name	start_time	end_time	activity_time	resource	replication
:-----	-----:	-----:	-----:	:-----	-----:
Student1	5.156790	5.43657	0.2797801	MalWart	1
Student3	9.106437	11.49592	2.3894828	MalWart	1
Student3	11.495920	12.76900	1.2730851	JHBunt	1
Student8	20.950618	23.24390	2.2932834	MalWart	1
Student2	23.704085	24.68430	0.9802124	MalWart	1
Student1	5.436570	25.34722	19.9106486	JHBunt	1

```
queueing_time = (end_time - start_time) - activity_time
```


Monitor the Attributes Data

- Next, let us inspect the rows in the 'mon_attributes' table.

```
knitr::kable(tail(mon_attributes))
```

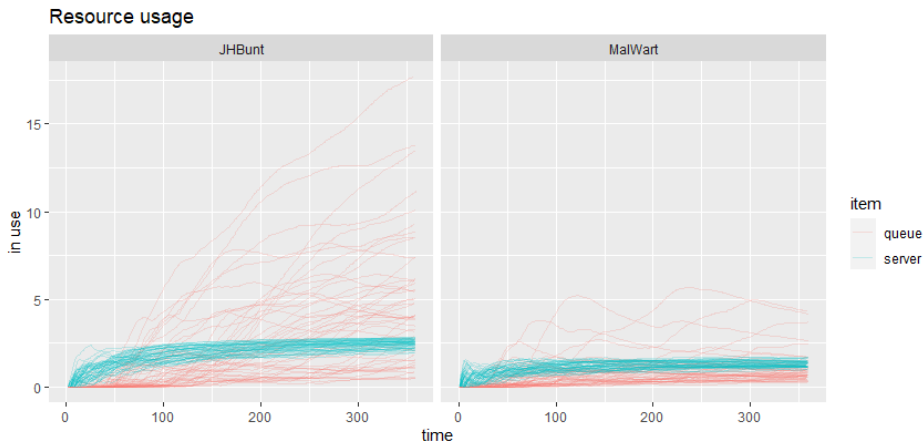
	time	name	key	value	replication
:-----	-----:	:-----	:----	-----:	-----:
13367	352.5556	Student169	type	1	50
13368	352.6140	Student170	type	1	50
13369	355.8731	Student161	type	2	50
13370	357.0327	Student171	type	1	50
13371	358.1386	Student172	type	1	50
13372	358.6568	Student167	type	2	50

- In total, there are 3 types of students.

Visualise the Resources Data

- To address the question of queue lengths at the two booths, we can begin with a plot.

```
plot(mon_resources, metric="usage", items=c("queue", "server"),  
     limits=FALSE)
```

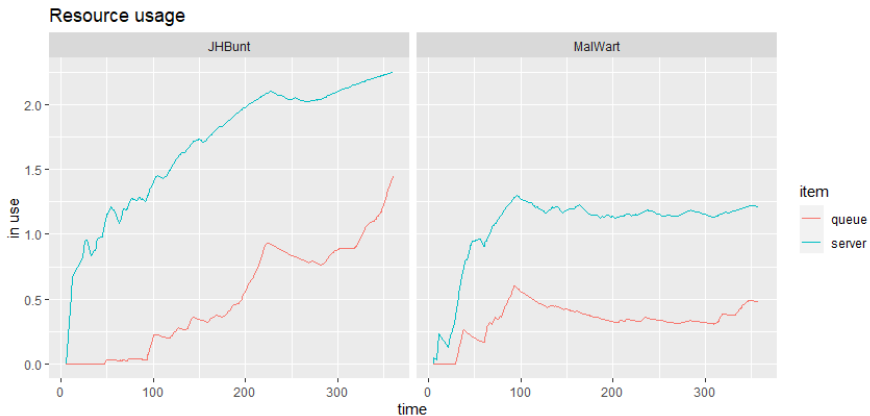


Visualise the Resources Data

cont'd

- To zoom into one specific simulation, say, the first replication, we can use the following code.

```
plot(mon_resources[mon_resources$replication == 1, ],  
     items=c("queue", "server"), limits=FALSE)
```

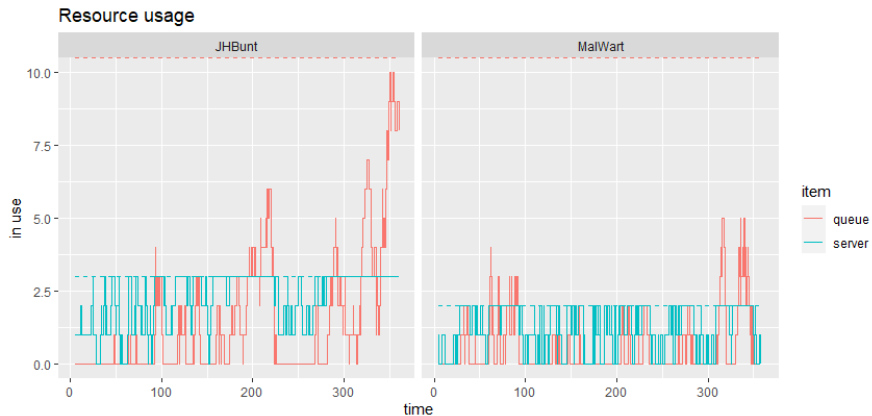


Visualise the Resources Data

cont'd

- If our interest is the instantaneous number of students in the queue, we can use the following code.

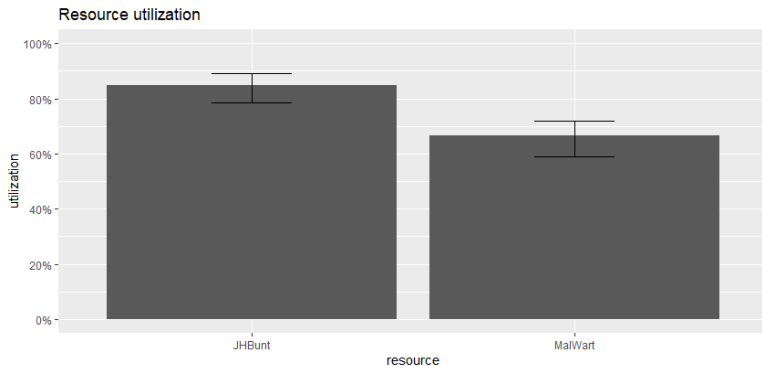
```
plot(mon_resources[mon_resources$replication == 1, ],  
     items=c("queue", "server"), limits=FALSE, step = TRUE)
```



Visualise the Resources Data

cont'd

```
plot(mon_resources , metric="utilization")
```



- In conclusion, the utilisation of 3 recruiters at the JHBunt booth is close to 85%, and the utilisation of 2 recruiters at the Malwart booth is slightly above 65%.

Utilise the Arrivals Data

to compute the waiting time at booths

- The arrivals data contain all the information we need to compute the waiting time for each student.
- To answer the last question on the mean waiting time at booths, our approach is going to be as follows:
 - ▶ We first write a simple function to extract the summary measure that we need for a single replication.
 - ▶ We next split the data frame by the replication number and use *sapply* to call this function on each sub data frame.

Waiting Time at Booths

define a function, split the data frame, and calculate the mean for each replication

- Our function is going to take in a data frame, and compute the mean waiting time for all students in that particular replication.

```
ave_wait_time <- function(df) {  
  mean(df$end_time - df$start_time - df$activity_time)  
}
```

- To split the arrivals data frame, we can use the ***split*** function from R. It returns a list of data frames, which we can then feed into ***sapply***.

```
s_out <- split(mon_arrivals, ~replication)  
w_vec <- sapply(s_out, ave_wait_time)
```

- ***w_vec*** records a vector of 50 values, which are some mean waiting time of students over the course of a 6-hour mixer, for each replication.

```
mean(w_vec)
```

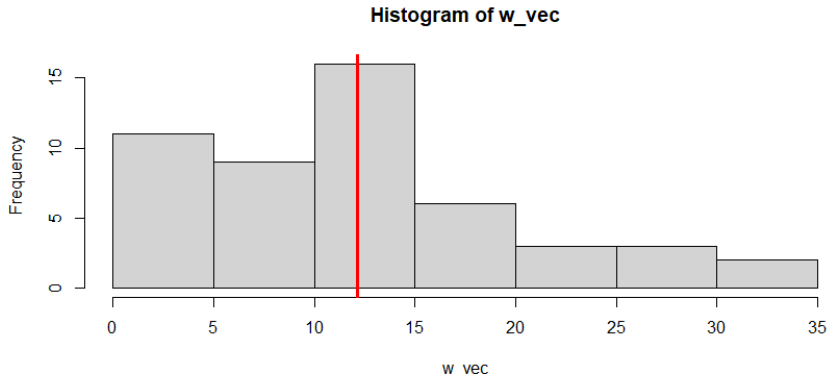
```
[1] 12.1311
```

Waiting Time at Booths

visualise the mean waiting time across the replications

- We can check the distribution of the mean waiting time across the replications.

```
hist(w_vec)
abline(v = mean(w_vec), col = "red", lwd = 3)
```



Waiting Time at Booths

calculate the standard normal-based 95% confidence interval

- We can compute a confidence interval to study the mean wait time of students.

```
summary(w_vec)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.926	6.118	10.481	12.131	16.066	34.994

```
ci_95 <- c(mean(w_vec) + qnorm(0.025)*sd(w_vec)/sqrt(length(w_vec)),  
           mean(w_vec) - qnorm(0.025)*sd(w_vec)/sqrt(length(w_vec)))  
ci_95
```

```
[1] 9.894196 14.367997
```

- We are 95% confident that the population mean wait time is between 9.89 and 14.37 minutes.

Decision Time and Future Plan

- From the earlier results, it is clear that the booths are being under-utilised.
- As an organiser, we have a powerful tool, Simulation, in our hands.
- We could experiment with several ways to make our operation more efficient.
 - ▶ We could, for instance, increase or reduce the number of recruiters at each booth, and see how that affects the waiting times.
 - ▶ If our priority is the utilisation, we could either keep the current arrangement, or slightly reduce the number of recruiters.
 - ▶ If our priority is to further reduce the mean waiting time, we could possibly increase the number of recruiters.
 - ▶ With a little more data manipulation, we can compute time-averaged numbers of wandering students to see if they are taking up a lot of physical space at the mixer.

Summary

In this video, we have:

- ▶ Fetched the monitor data: arrivals, attributes and resources.
- ▶ Visualised the monitor data.
- ▶ Utilised the monitor data to answer our research questions.

Overall,

we hope that this week's set of videos have given you a good indication of the overall process of setting up, executing, and studying the output of a discrete event simulation using R.

References



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