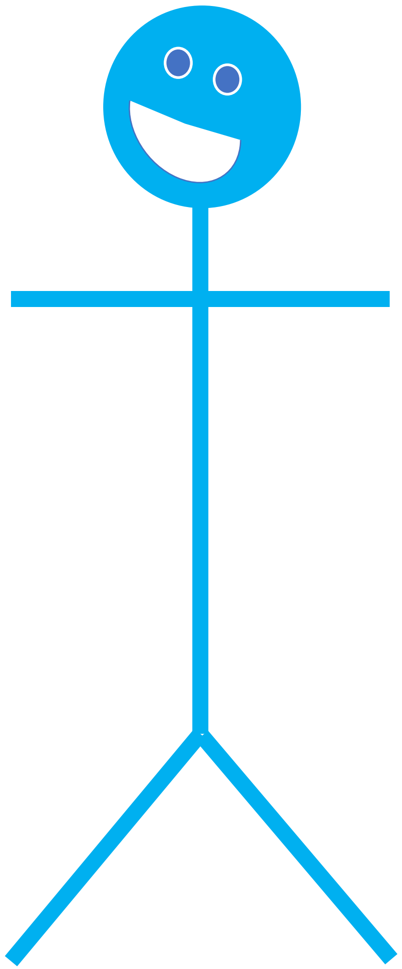
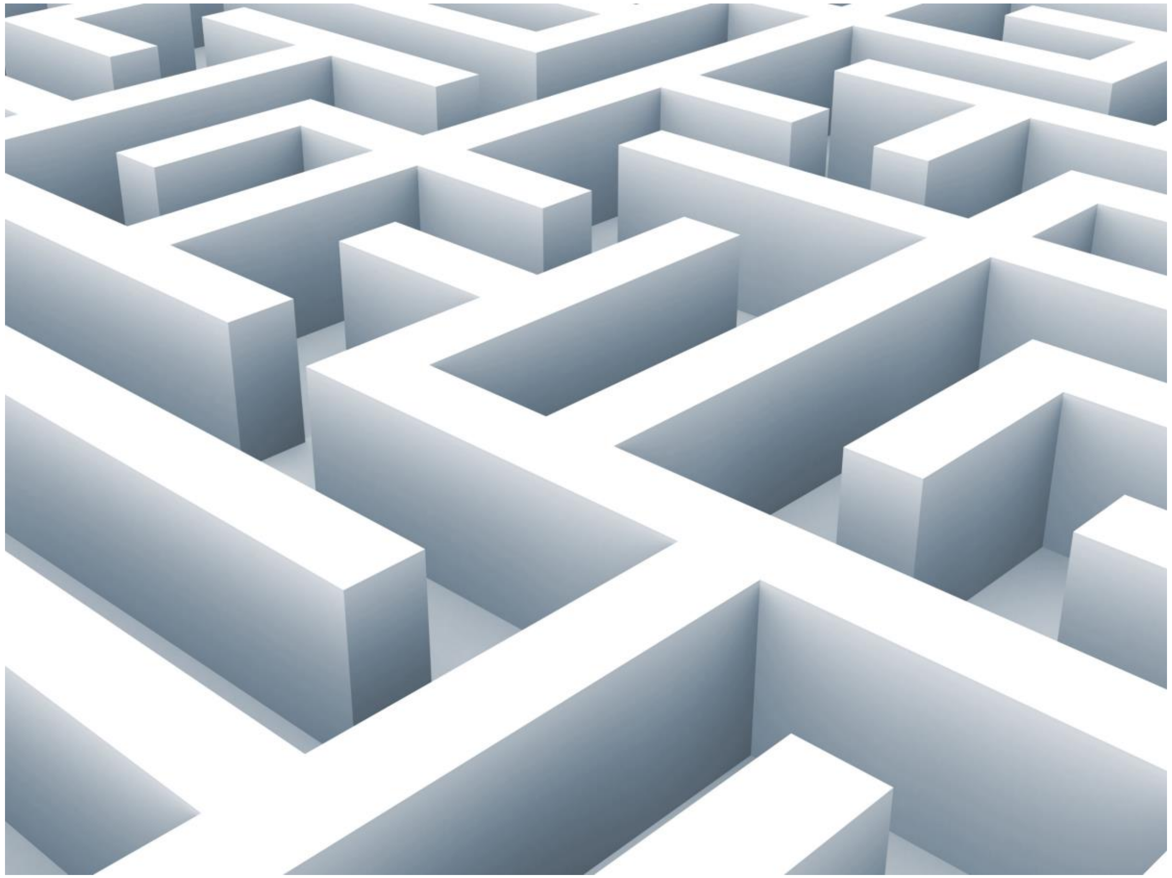
Stochastic Simulation & ML



Ray Bosman – Machine Learning Engineer - Derivco

Wind up toys – let loose in a system



Random Numbers

-runif(100,0,1)

Stochastic Simulation

-Programming with random numbers

-Replicate existing systems

-Experimentation

Structure

-Clock

-Programmed rules and outcomes per interval

-State management

-Run many trials

-Collect results

Example

Odds or Evens

```
step <- 100

dice <- c()

for (x in 1:step) {
  outcome <- sample(c(1,2,3,4,5,6), 1, prob=c(1/6,1/6,1/6,1/6,1/6,1/6))
  dice<-c(dice,outcome)
}

sum(dice %% 2 == 0)/step
```

Example

Result is **0.45**

or

45% of outcomes are **even** in 100 spins

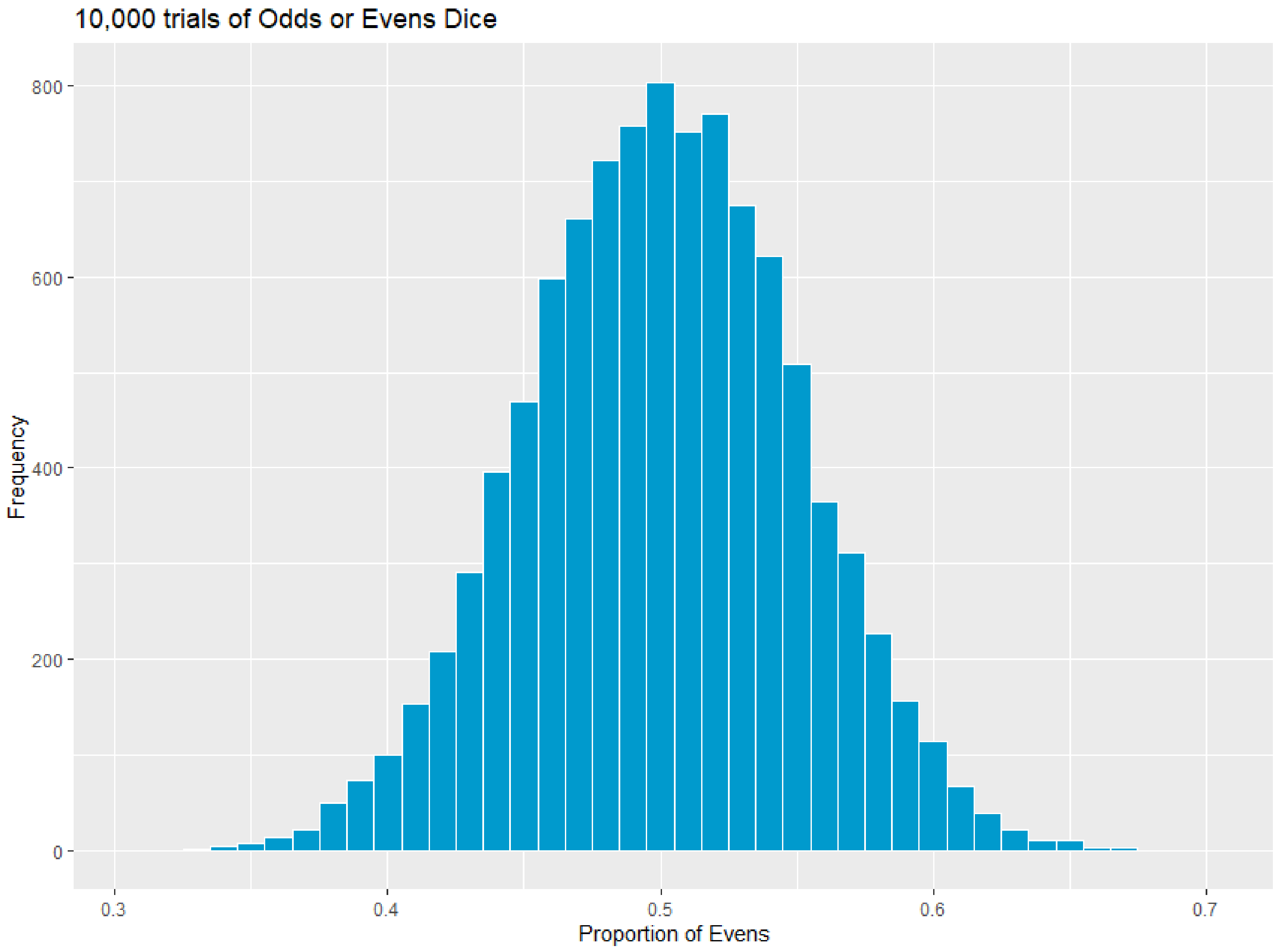
Example

Odds or Evens with many trials

```
library(ggplot2)

trials <- 10000
step <- 100

result <- c()

for (x in 1:trials) {

    dice <- c()

    for (y in 1:step) {
        outcome <- sample(c(1,2,3,4,5,6), 1, prob=c(1/6,1/6,1/6,1/6,1/6,1/6))
        dice<-c(dice,outcome)
    }

    result <- c(result,sum(dice %% 2 == 0)/step)
}

dfResult <- data.frame(x=result)

ggplot(data=dfResult, aes(x = x)) + geom_histogram(color = "white", fill = "deepskyblue3", binwidth = .01) +
labs(title="10,000 trials of Odds or Evens Dice") + xlab("Proportion of Evens") + ylab("Frequency")

mean(dfResult$x)
```

Outcome

Average of ~0.5 (50%)



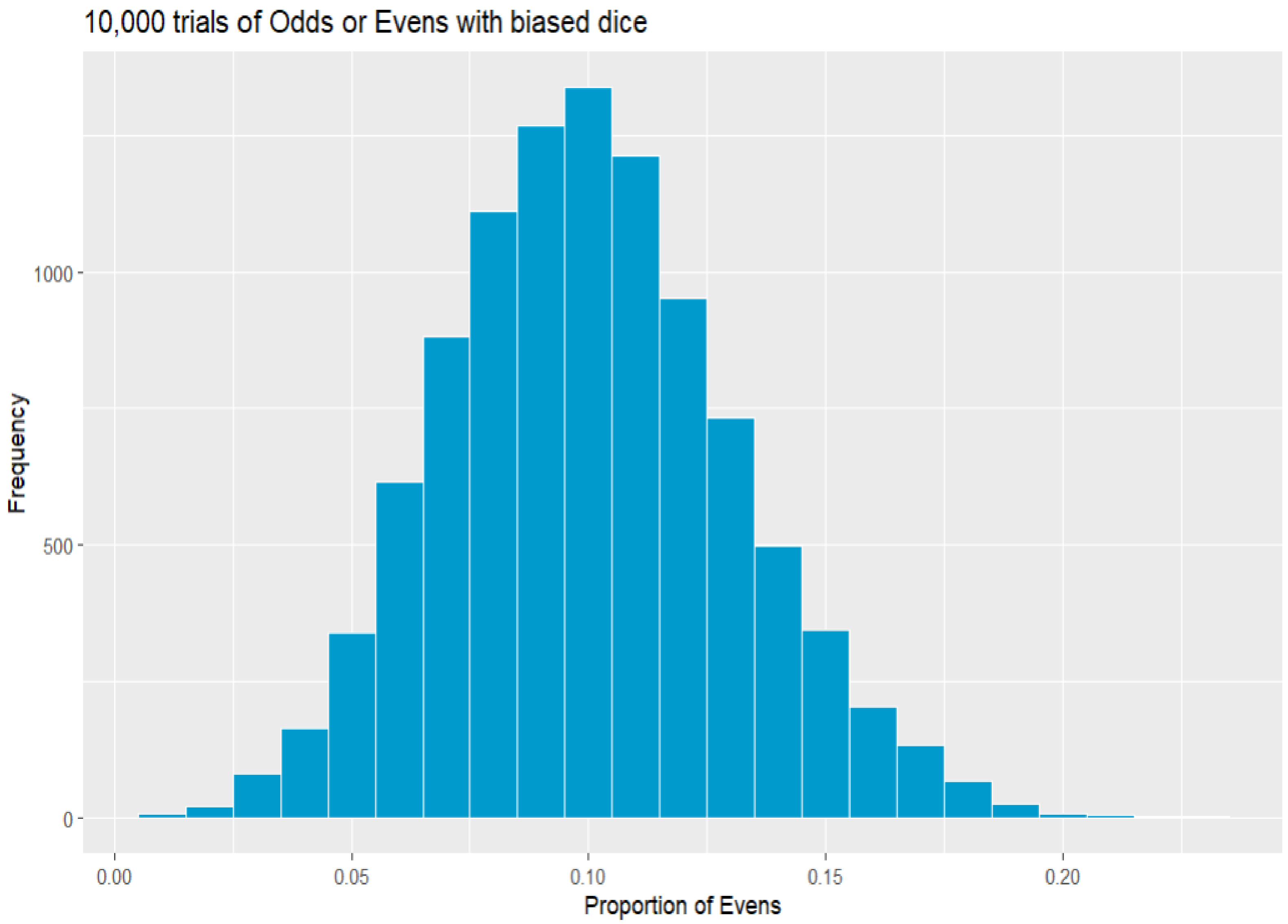
Examples

Odds or Evens with many trials & **biased dice**

```
library(ggplot2)

trials <- 10000
step <- 100

result <- c()

for (x in 1:trials) {

    dice <- c()

    for (y in 1:step) {
        outcome <- sample(c(1,2,3,4,5,6), 1, prob=c(1.8/6,.2/6,1.8/6,.2/6,1.8/6,.2/6))
        dice<-c(dice,outcome)
    }

    result <- c(result,sum(dice %% 2 == 0)/step)
}

dfResult <- data.frame(x=result)

ggplot(data=dfResult, aes(x = x)) + geom_histogram(color = "white", fill = "deepskyblue3", binwidth =
.01) + labs(title="10,000 trials of Odds or Evens with biased dice") + xlab("Proportion of Evens") +
ylab("Frequency")

mean(dfResult$x)
```

Outcome

Average of ~0.1 (10%)



Something more useful

Example Overview

-Programming represents the business

-Random numbers represent actor behaviour

Simulate Business Case

-Restaurants & Customers

-Repeated consumption, Experiential

-Diminishing returns

-Reasonable chance of departure

Business Details

-Actor signs up for free

-Discounts at selected options

-Restaurant can drive volume

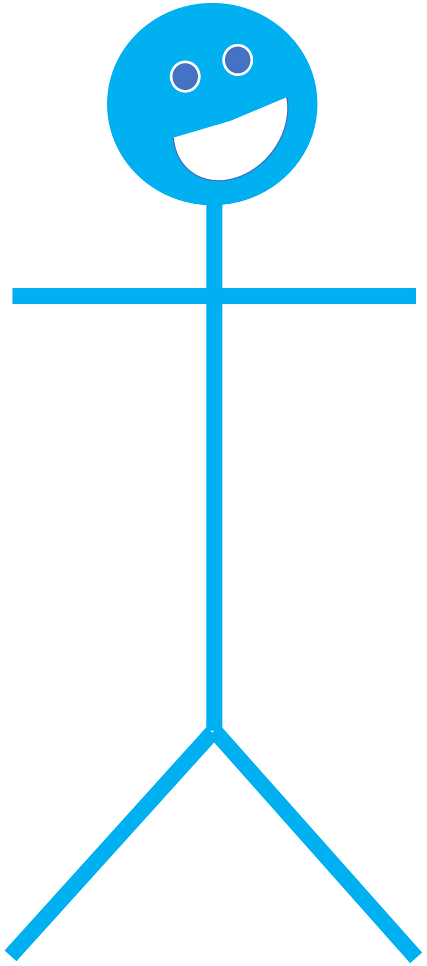
Diner
Riders

Diner ™
Riders

Actor

Diner™
Riders

Actor



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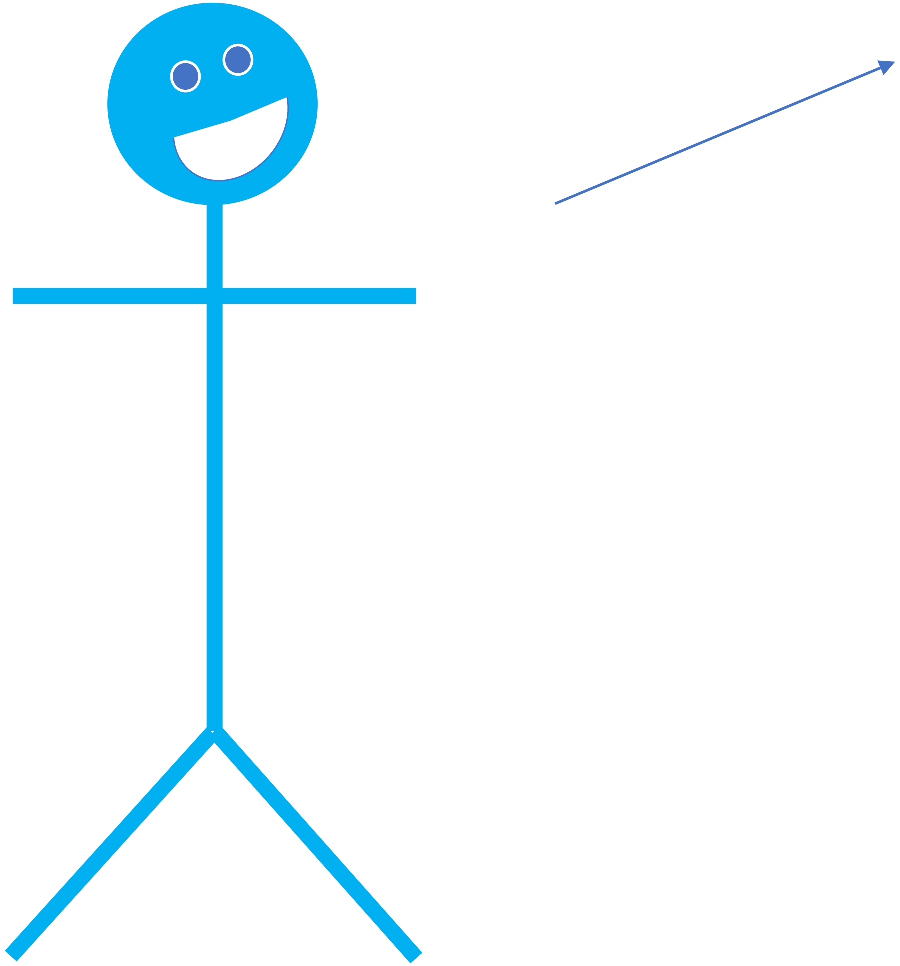
Actor Actions



Check schedule

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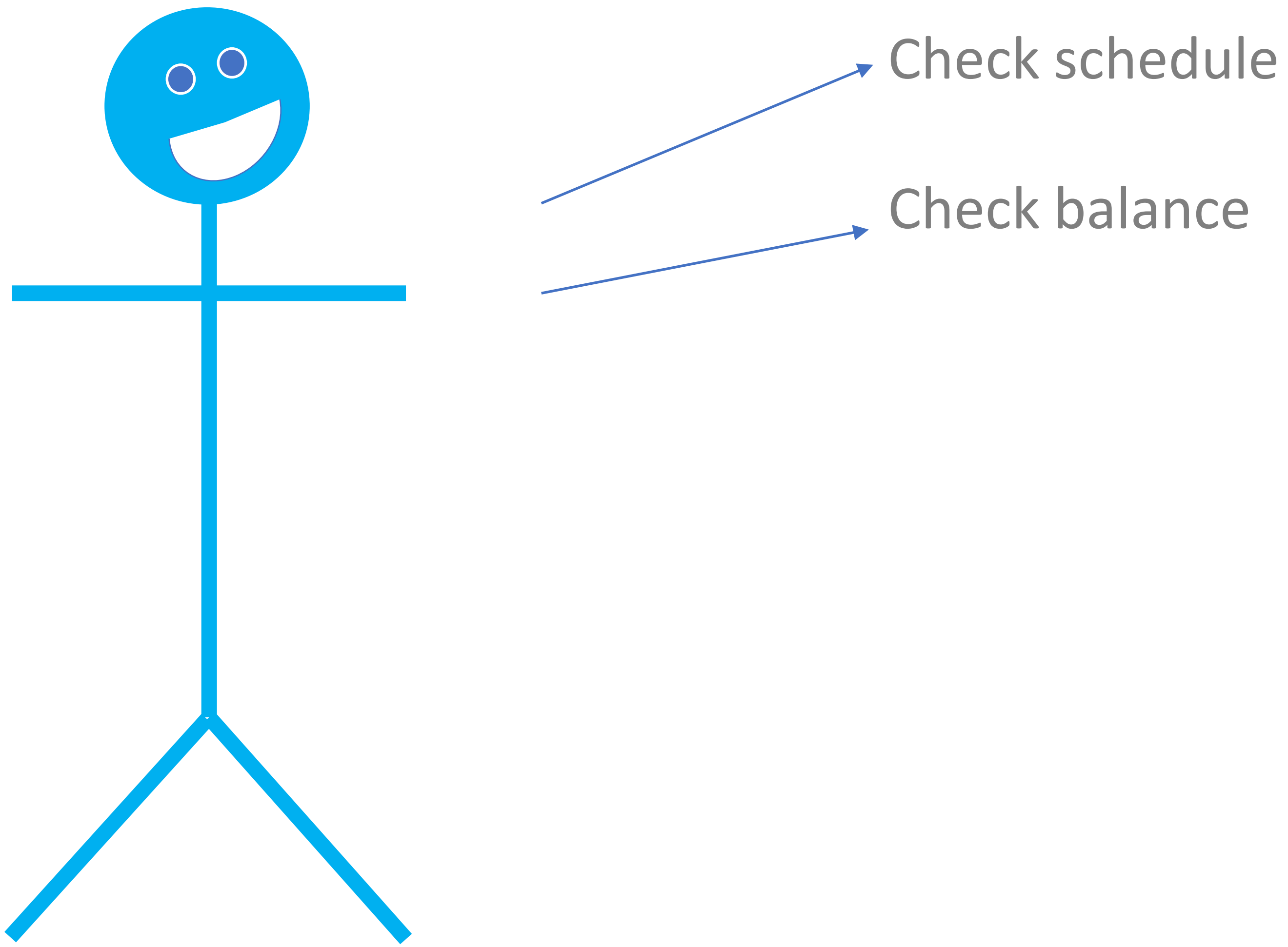
Actor Actions



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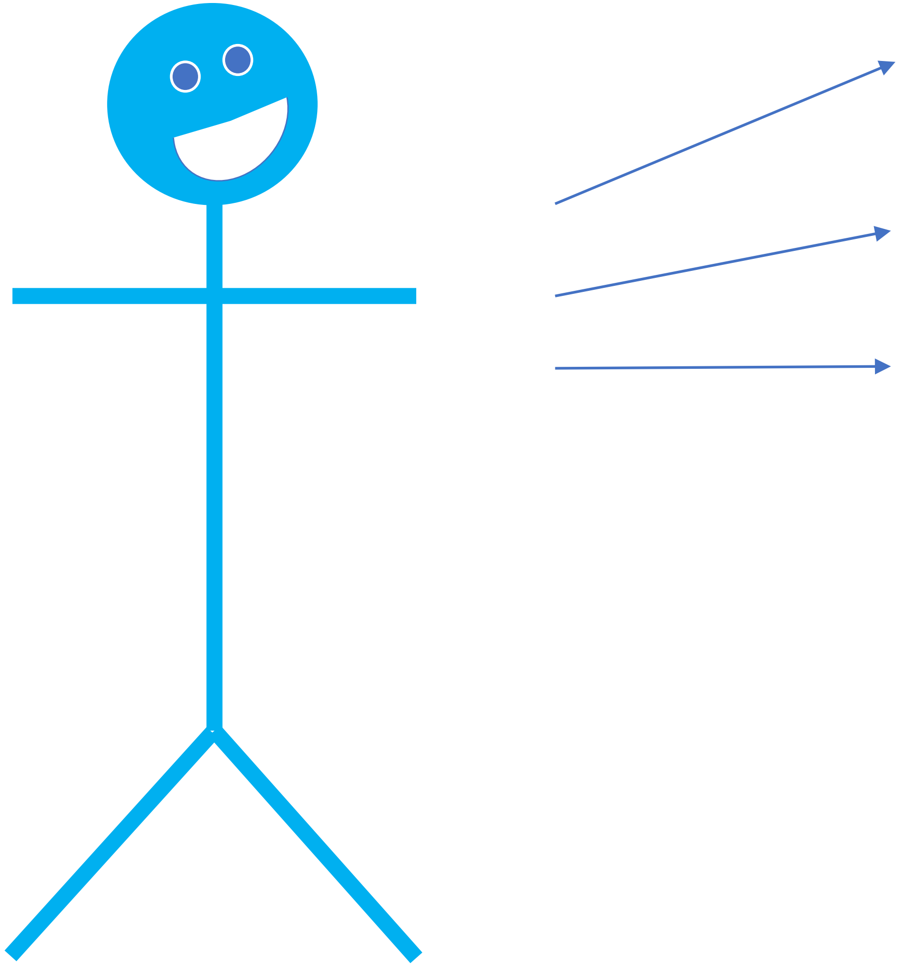
Actor Actions



- Check schedule
- Check balance
- Seek gratification

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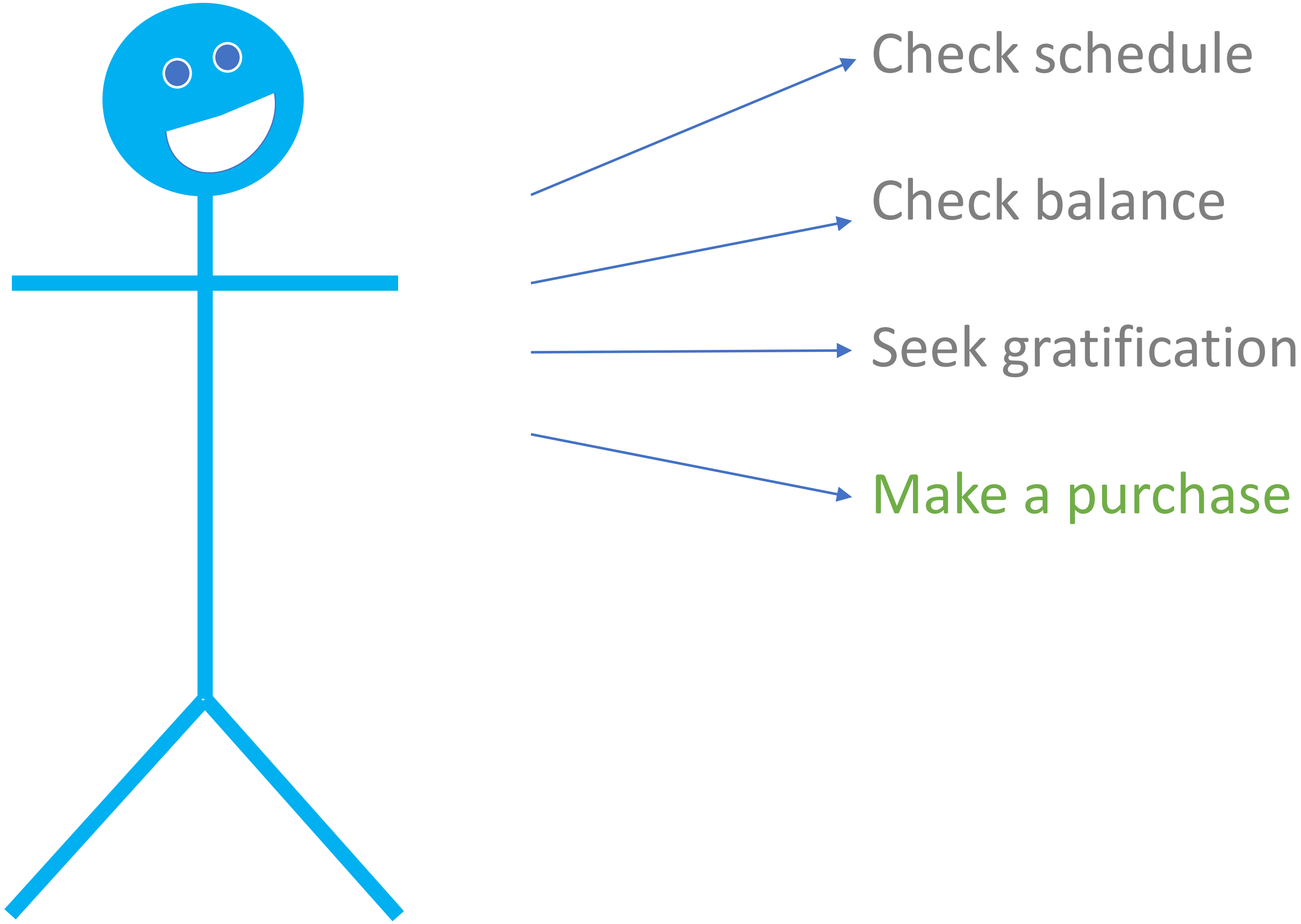
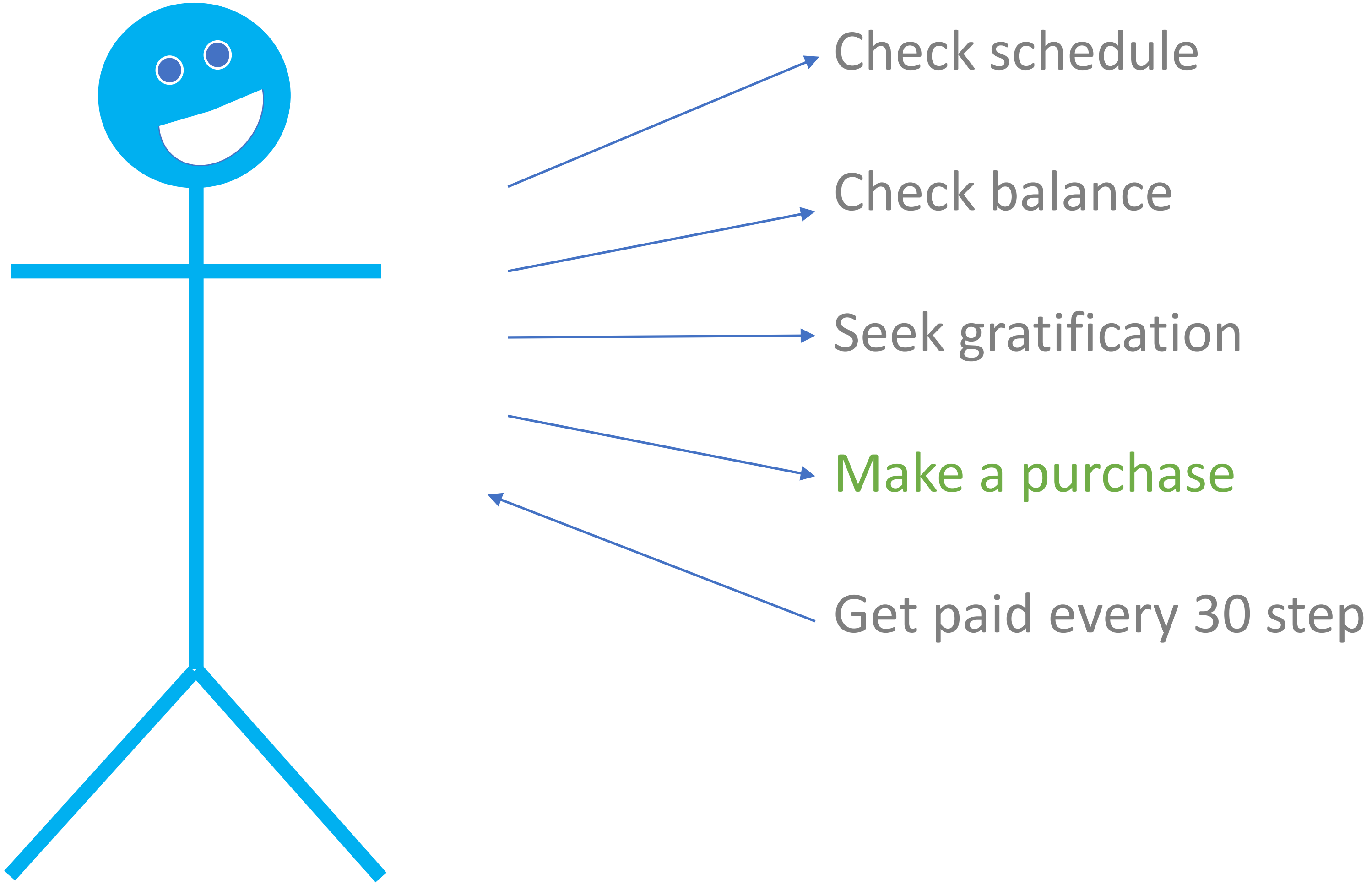
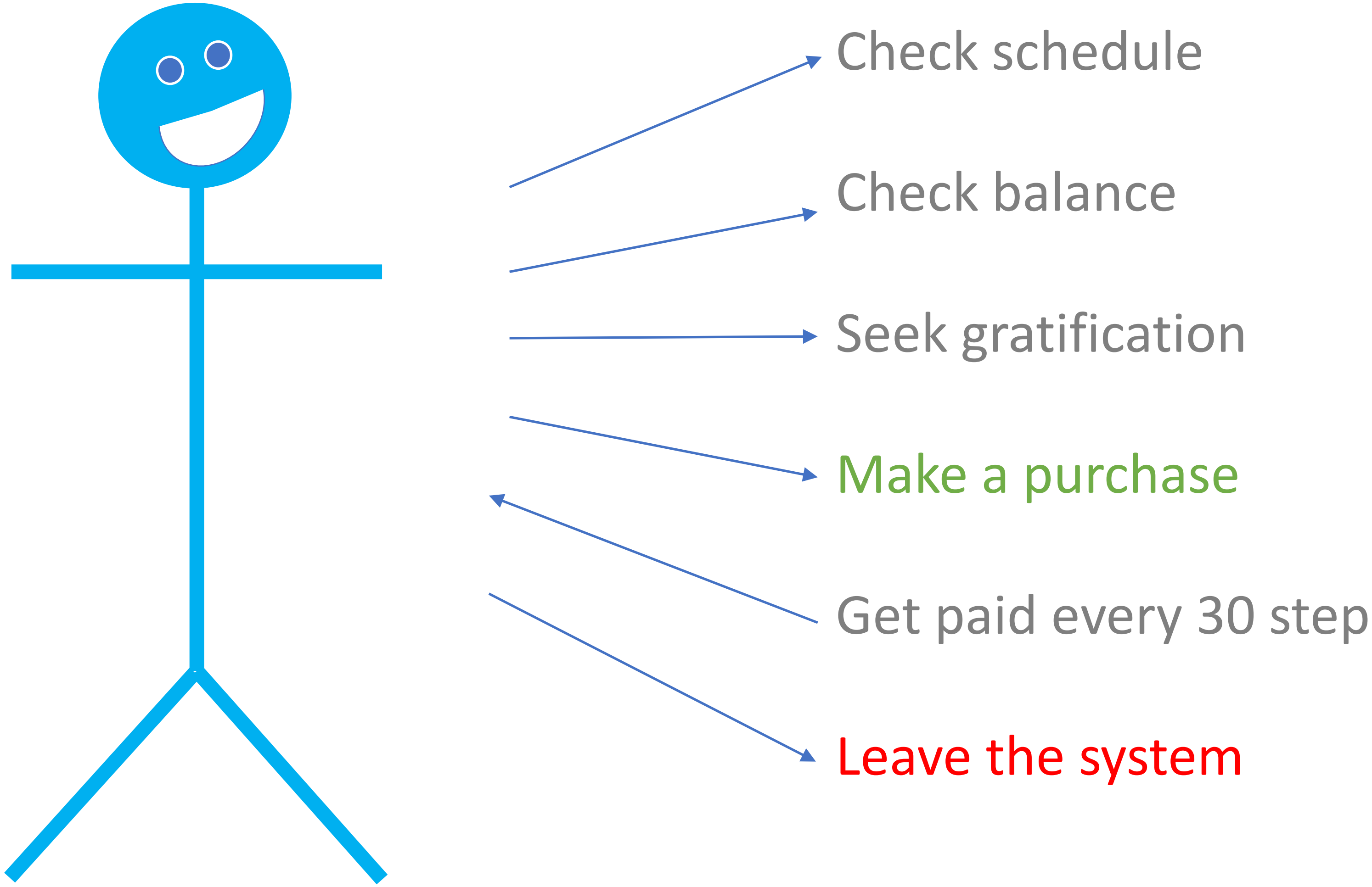
Actor Actions



Actor Actions



Actor Actions



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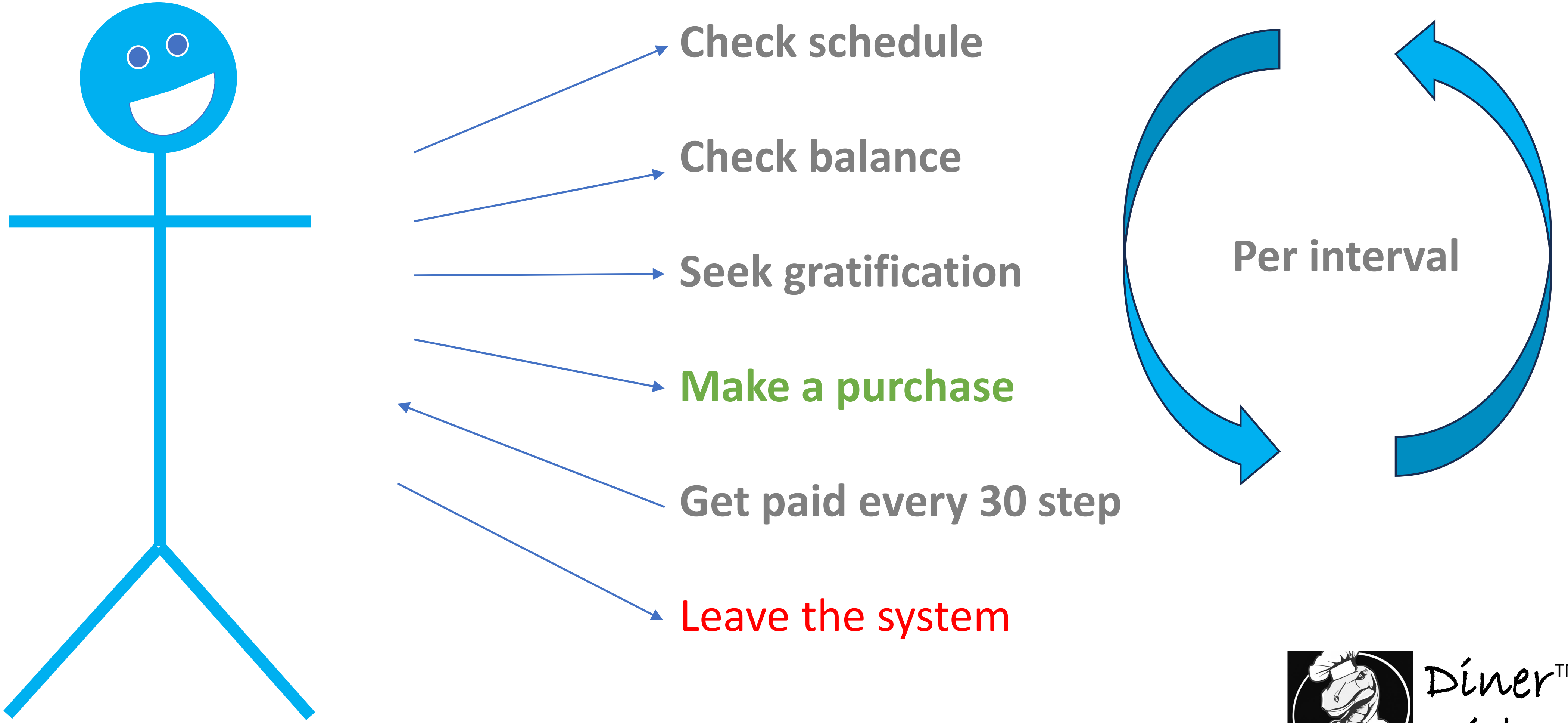
Actor Actions



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Actor Purchase Options

Name	Cost	Gratification
Option 1 (**Garage Pie**)	20	1
Option 2	50	2
Option 3	100	3
Option 4	300	4
Option 5	500	5
Option 6 (**Oyster Box**)	1000	6

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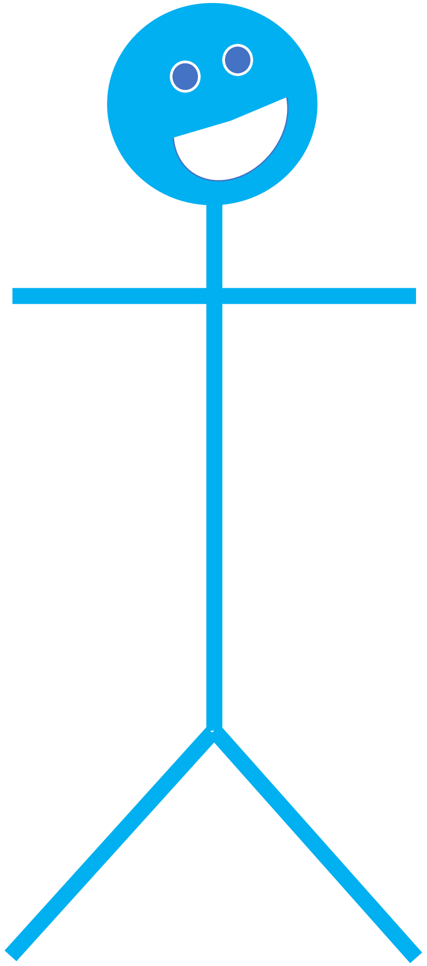
Actor



>Personal schedule

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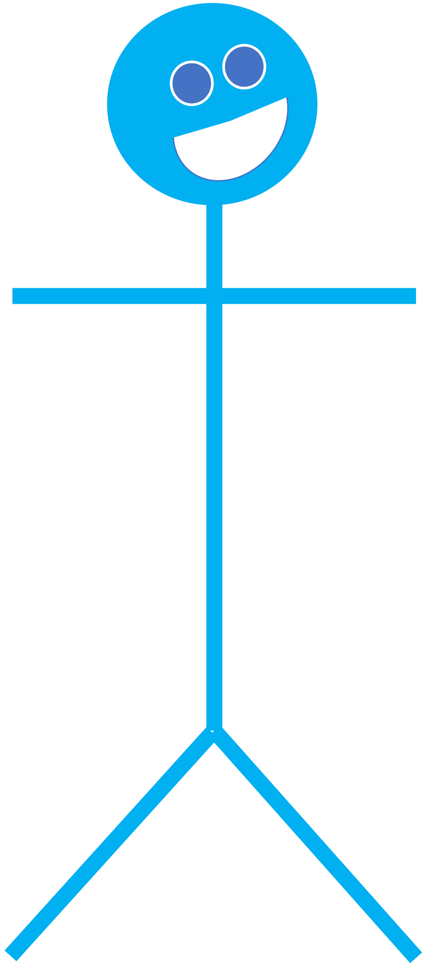
Personal Schedule



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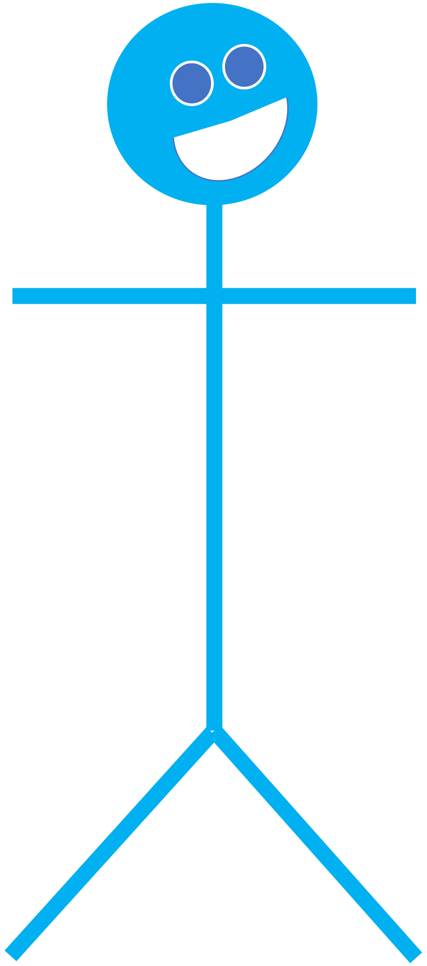
Personal Schedule



80% Chance of going out

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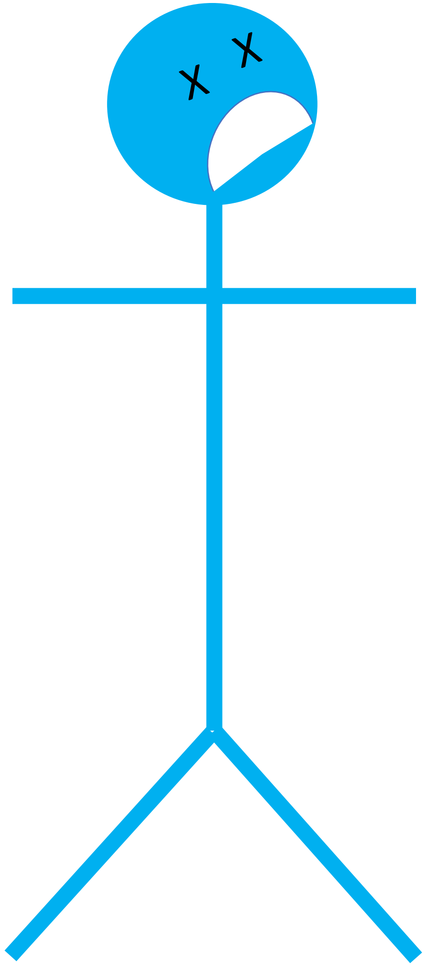
Personal Schedule



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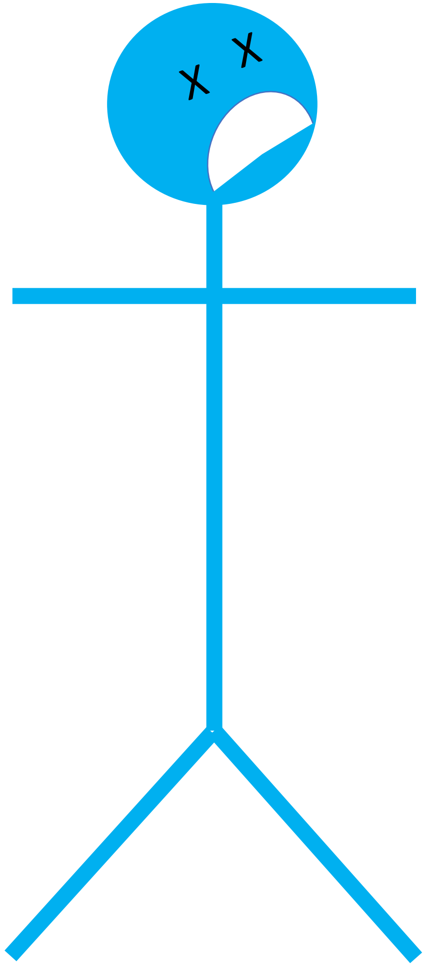
Personal Schedule



15% Chance of going out

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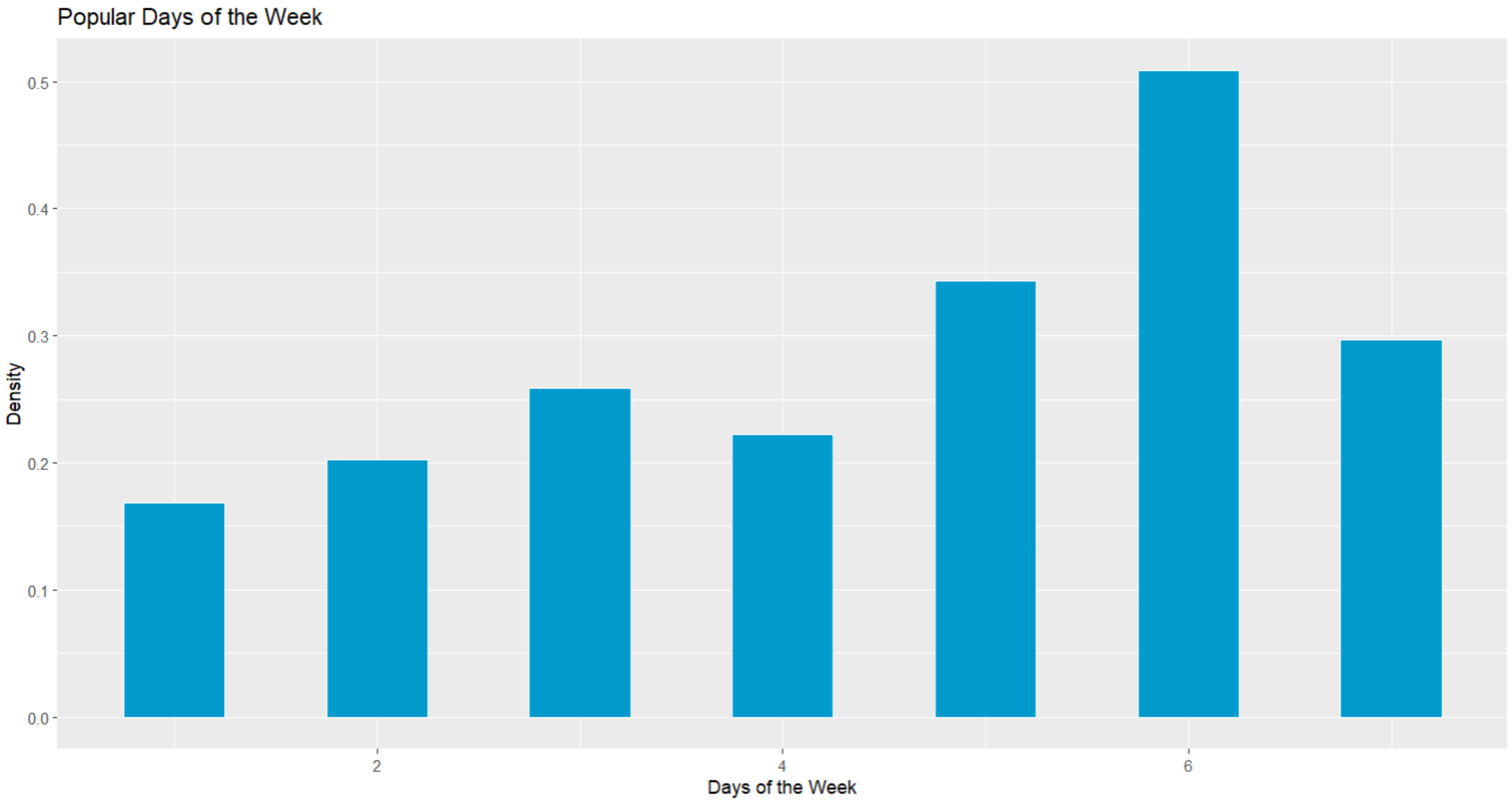
Personal Schedule



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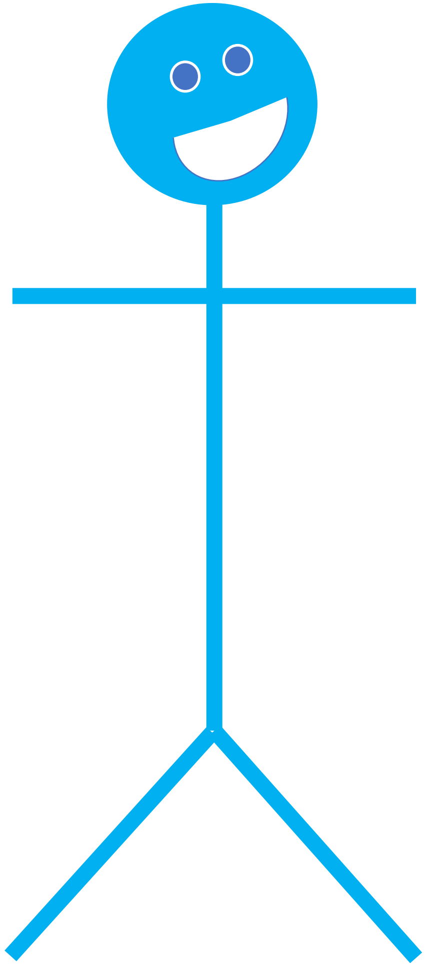
Actor



>Personal schedule

>Monthly entertainment budget

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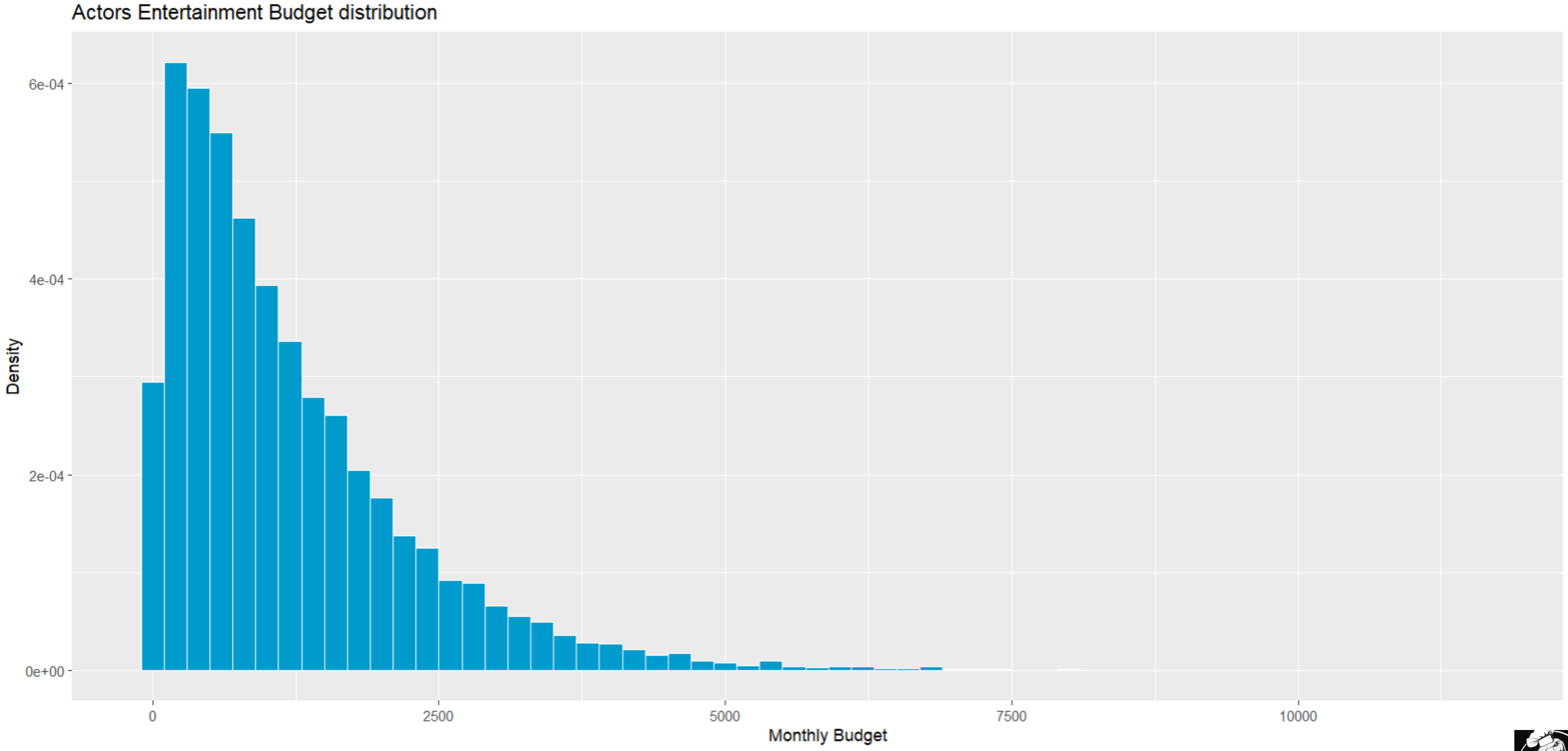
Monthly Actor Budget



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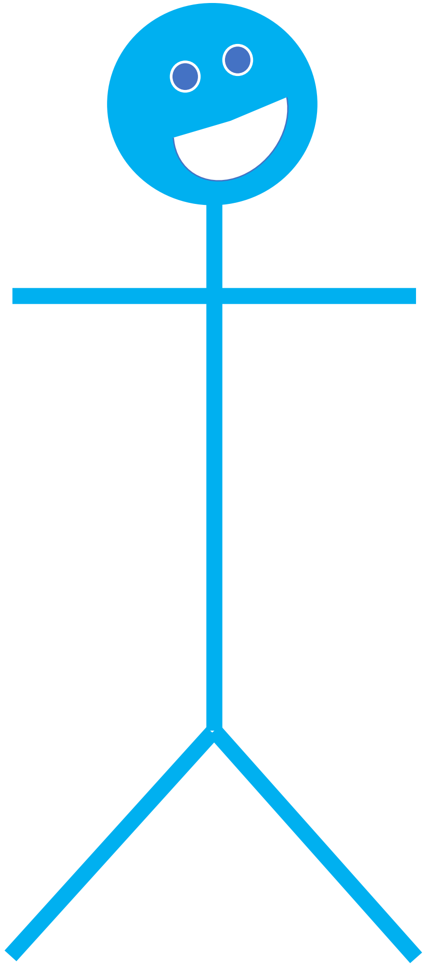
Actor



>Personal schedule

>Monthly entertainment budget

>Reward

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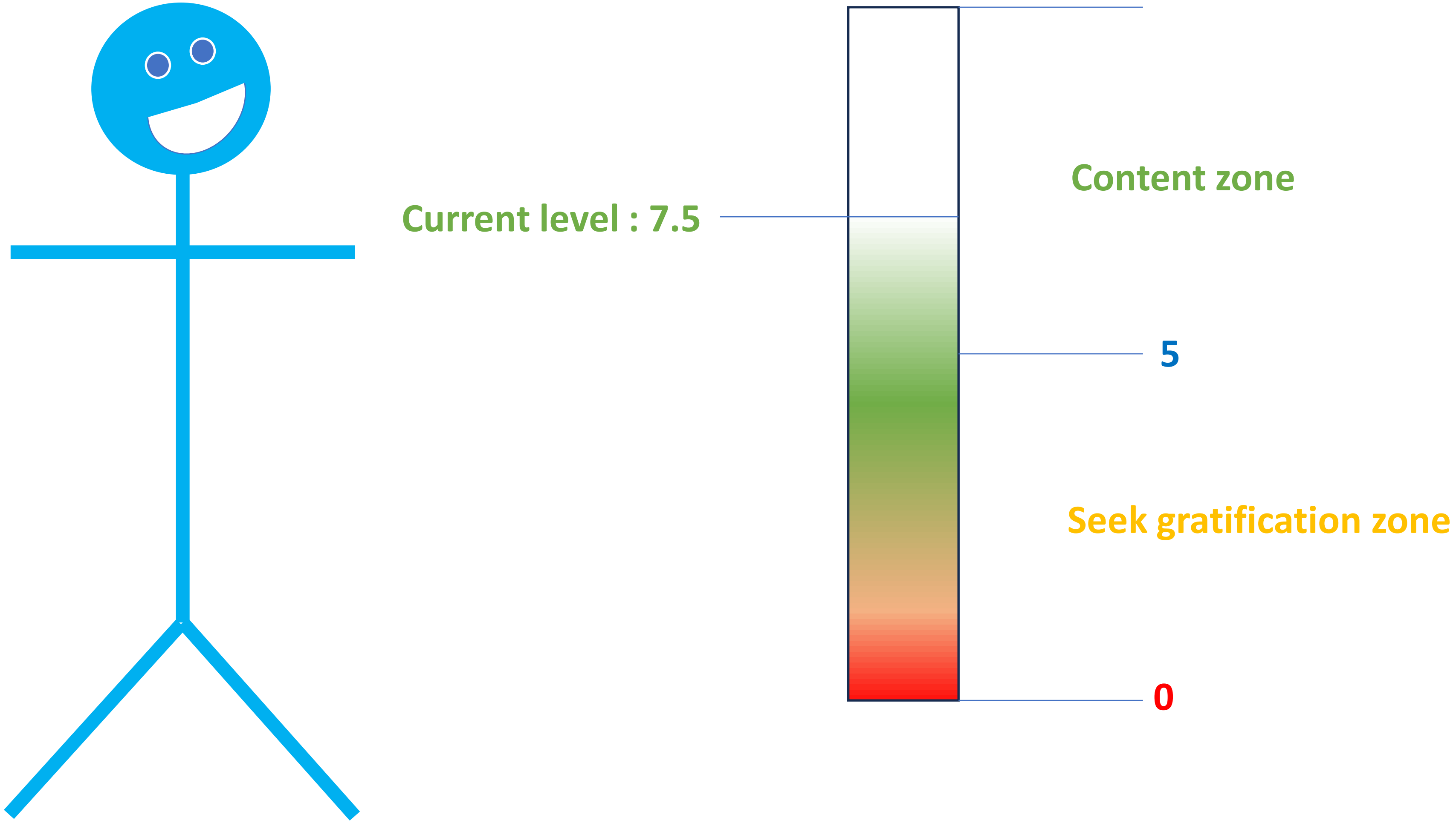
Reward



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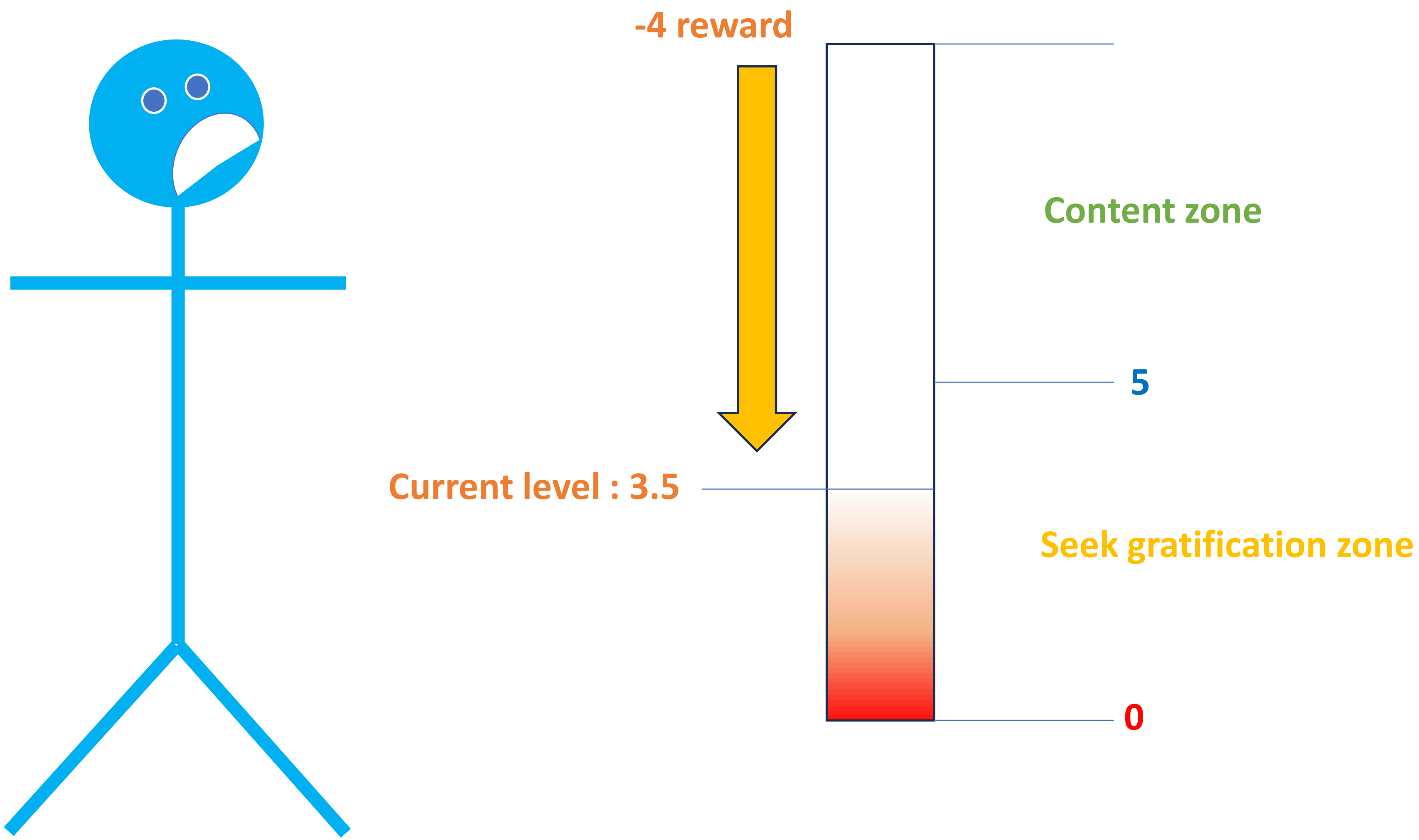
Reward



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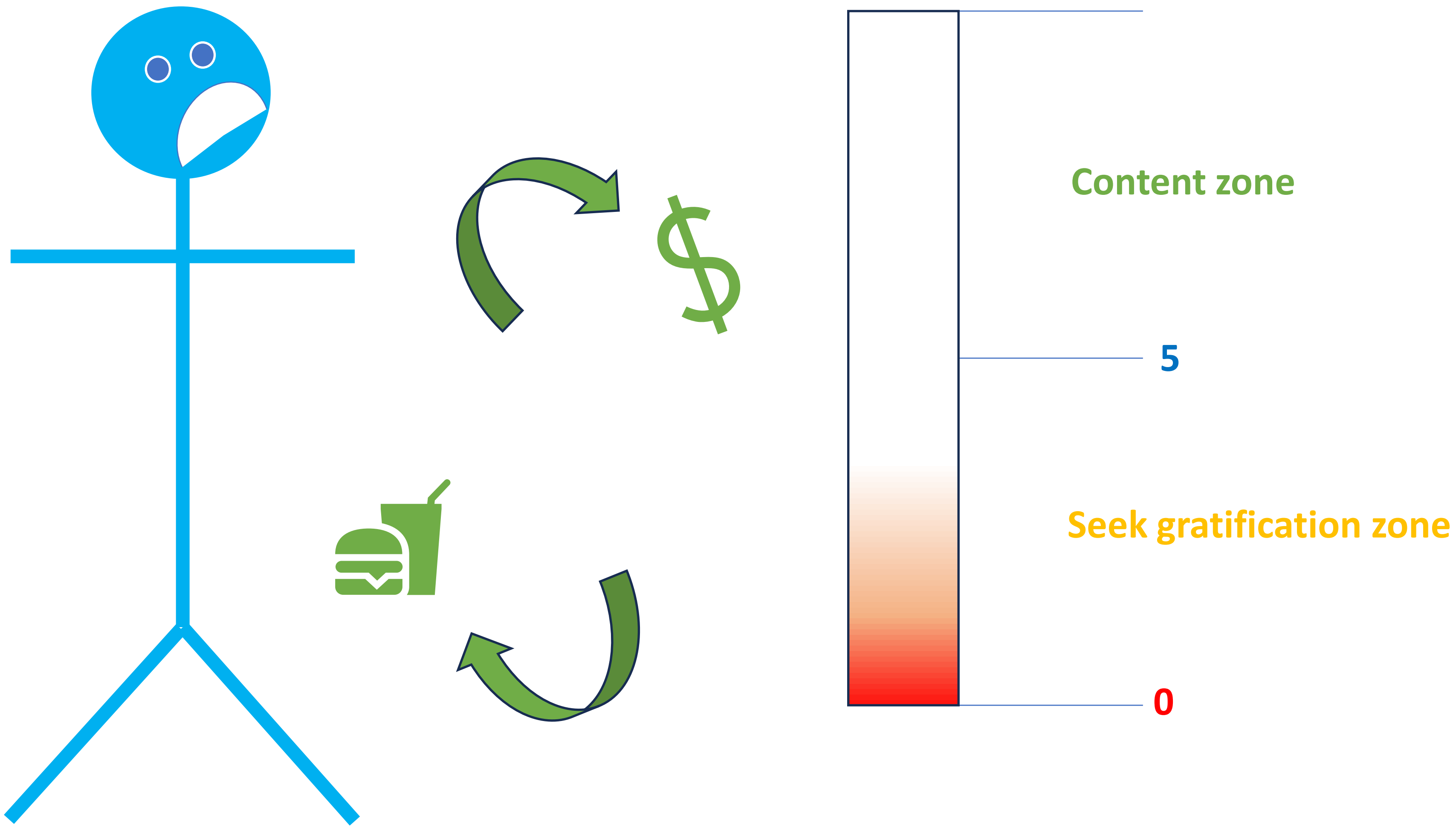
Reward



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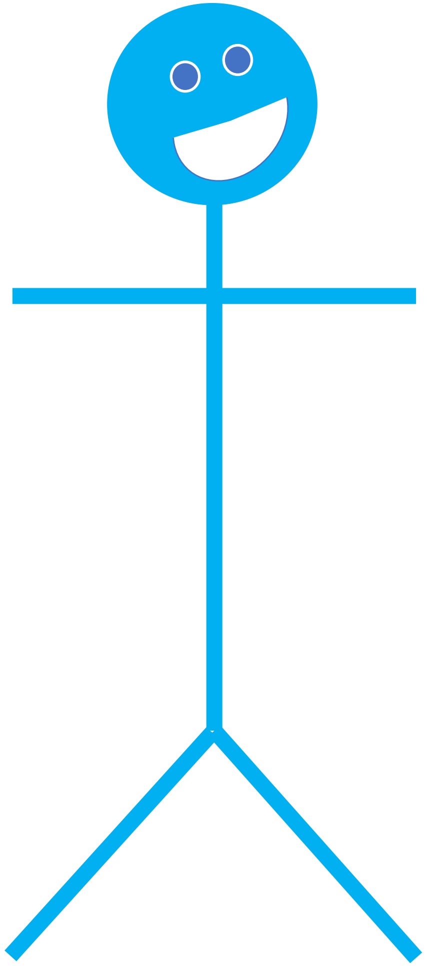
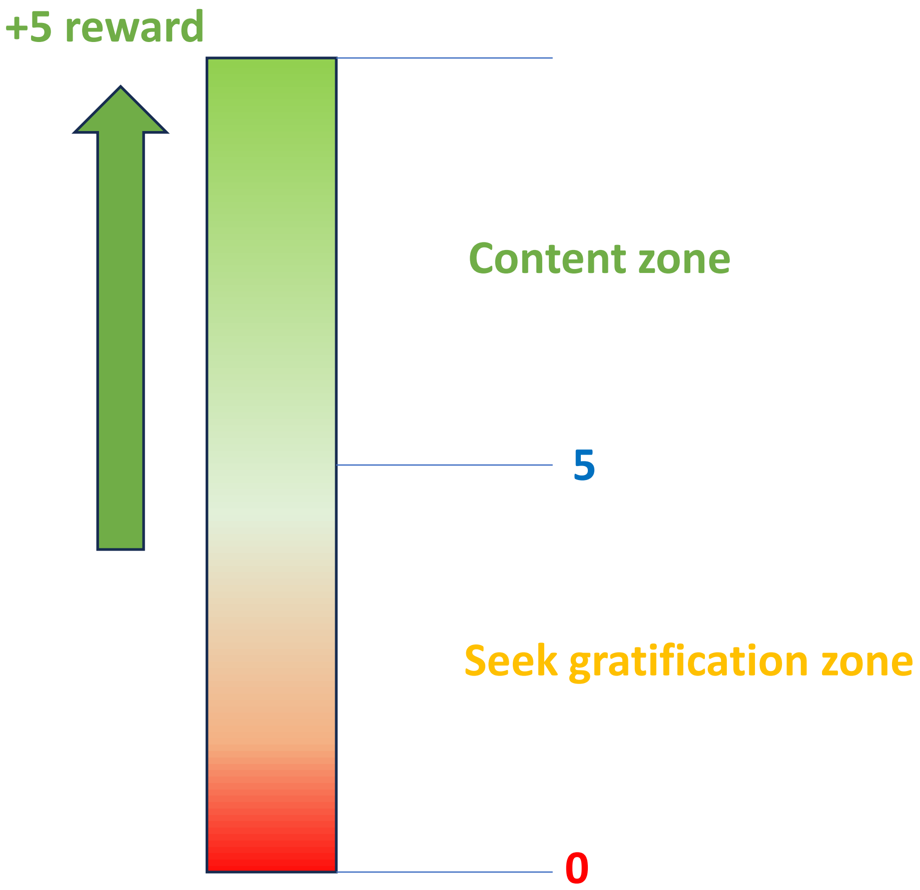
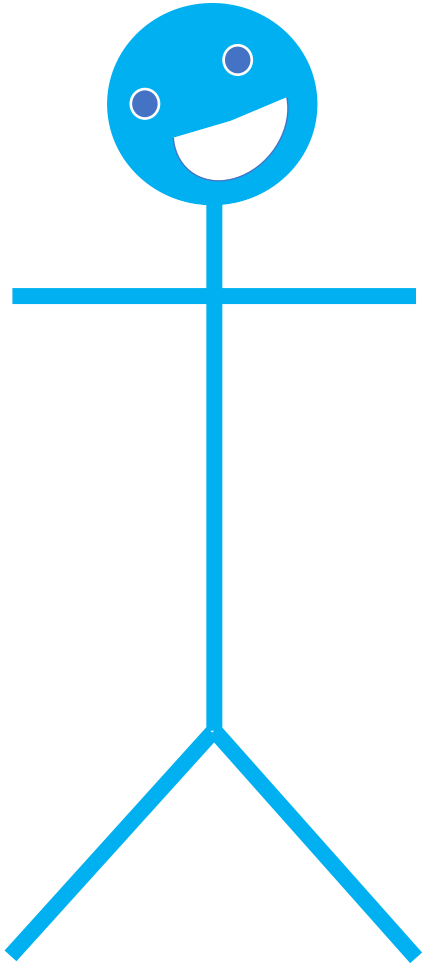
Reward





Actor



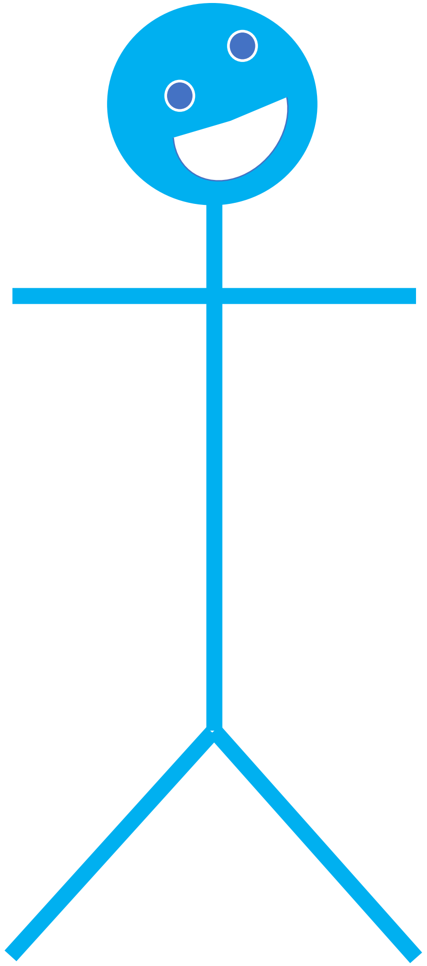
>Personal schedule

>Monthly entertainment budget

>Reward

>Reward degradation and repair

Actor



>Personal schedule

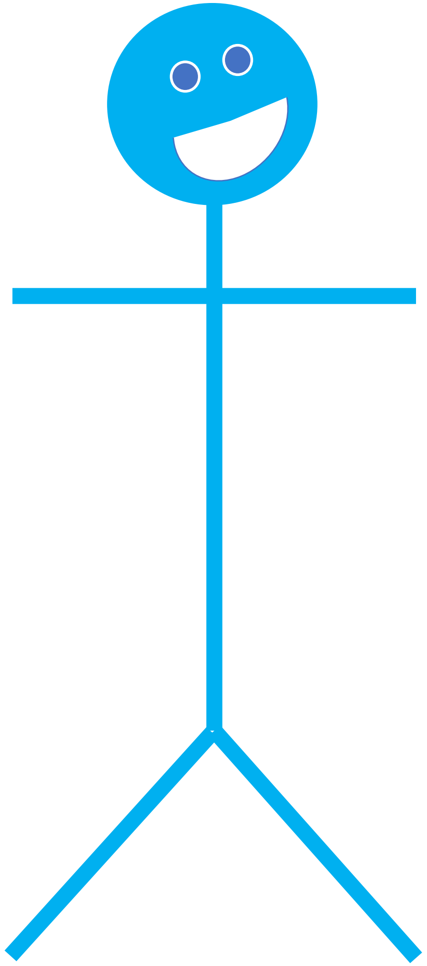
>Monthly entertainment budget

>Reward

>Reward degradation and repair

>Departure threshold

Actor



>Personal schedule (Uniform)

>Monthly entertainment budget (Gamma)

>Reward (5)

>Reward degradation and repair (Uniform)

>Departure threshold

Sequence of events

```
START :
    >Start loop 1 in 200

      >Instantiate 20 actors while day < 100

      >Loop through actors and compute each ones decisions for the day

      >Collect daily statistics

END
```

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Activities of actor

```
START :
    >decrement reward total

    reward level less than 0?

        >leave the service

    reward level less than threshold 5 ?

        Is the actors schedule free for the current day of the week?

            >Select option that is affordable and has the highest expected return on reward

            >Buy the option

            >Diminish option reward

            >Transfer reward to actor

END
```

Simulation Parameters

Simulation Run 1 : 200 days, 20 customers onboarded per day for 100 days **without** ML intervention

Train classifier using
time_since_last_action,cost,actions_taken,ticker,day,total_consumption,u_consumption

Simulation Run 3 : 200 days, 20 customers onboarded per day for 100 days **with** ML intervention

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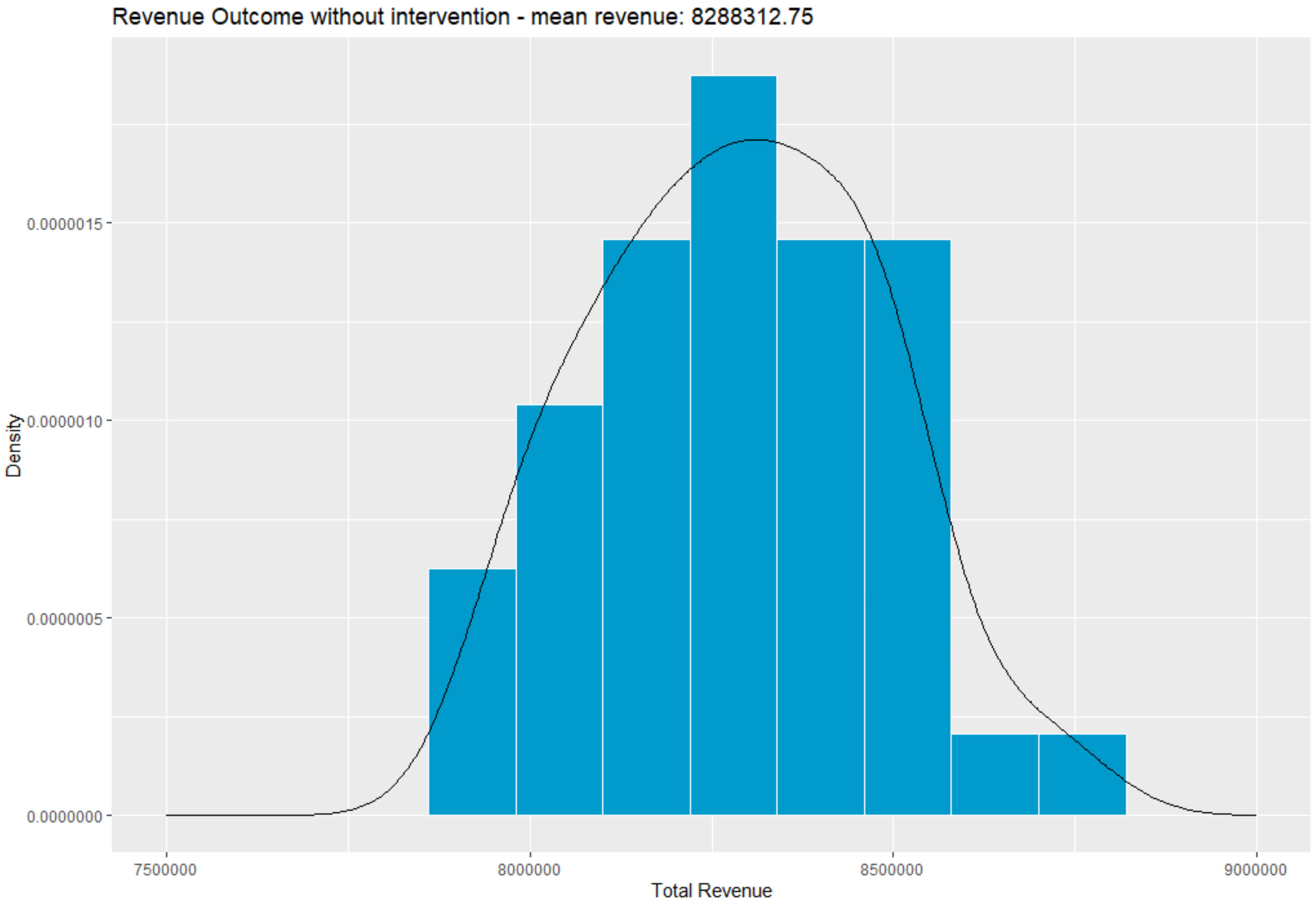
40 trials, revenue output



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Attrition Detection Variable Iiportance

	Overall
u_consumption	745.0947
ticker	697.8151
total_consumption	665.0622
actions_taken	428.8530
time_since_last_action	346.7254
cost	340.1042
day	192.3521

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Attrition Detection Model Performance

	REFERENCE		
PREDICTED	FALSE	TRUE	
FALSE	40101	352	
TRUE	81	221	

```
Precision : 0.7318
Recall    : 0.3857
F1        : 0.5

Total Accuracy : 0.99
```

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Model Implementation

On purchase : when score > 0.5 – unlock option 7

Activities of actor with treatment

```
START :
    >decrement reward total

    reward less than 0?

        >leave the service

    reward less than threshold 5 ?

        Is the actors schedule free for the current day of the week?
            Are they going to leave? (.5+)
              Reveal new high value offer - 100% chance of acceptance

            >Select option that is affordable and has the highest expected return on reward

            >Buy the option

            >Diminish option reward

            >Transfer reward to actor

END
```

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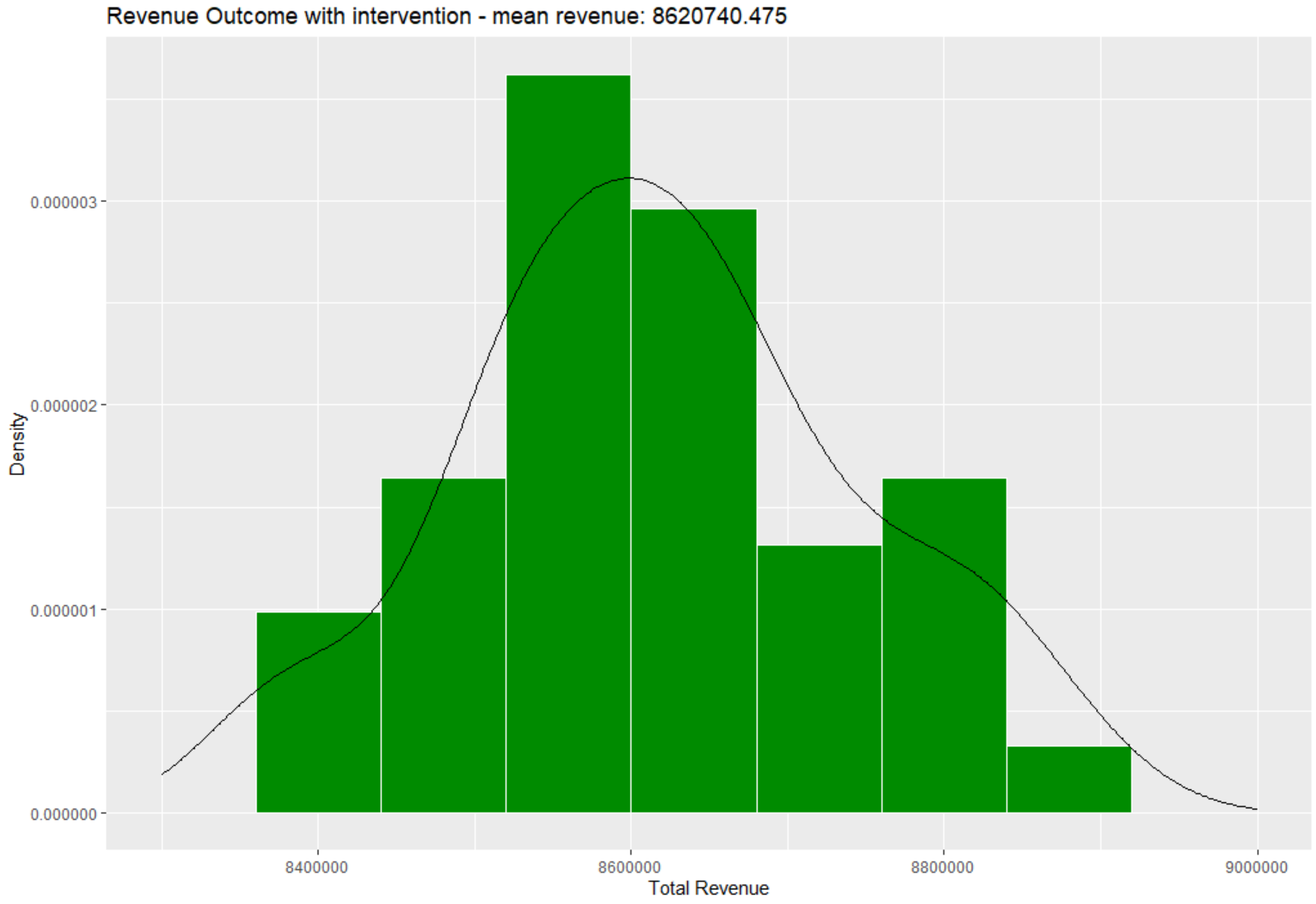
40 trials, revenue output with intervention



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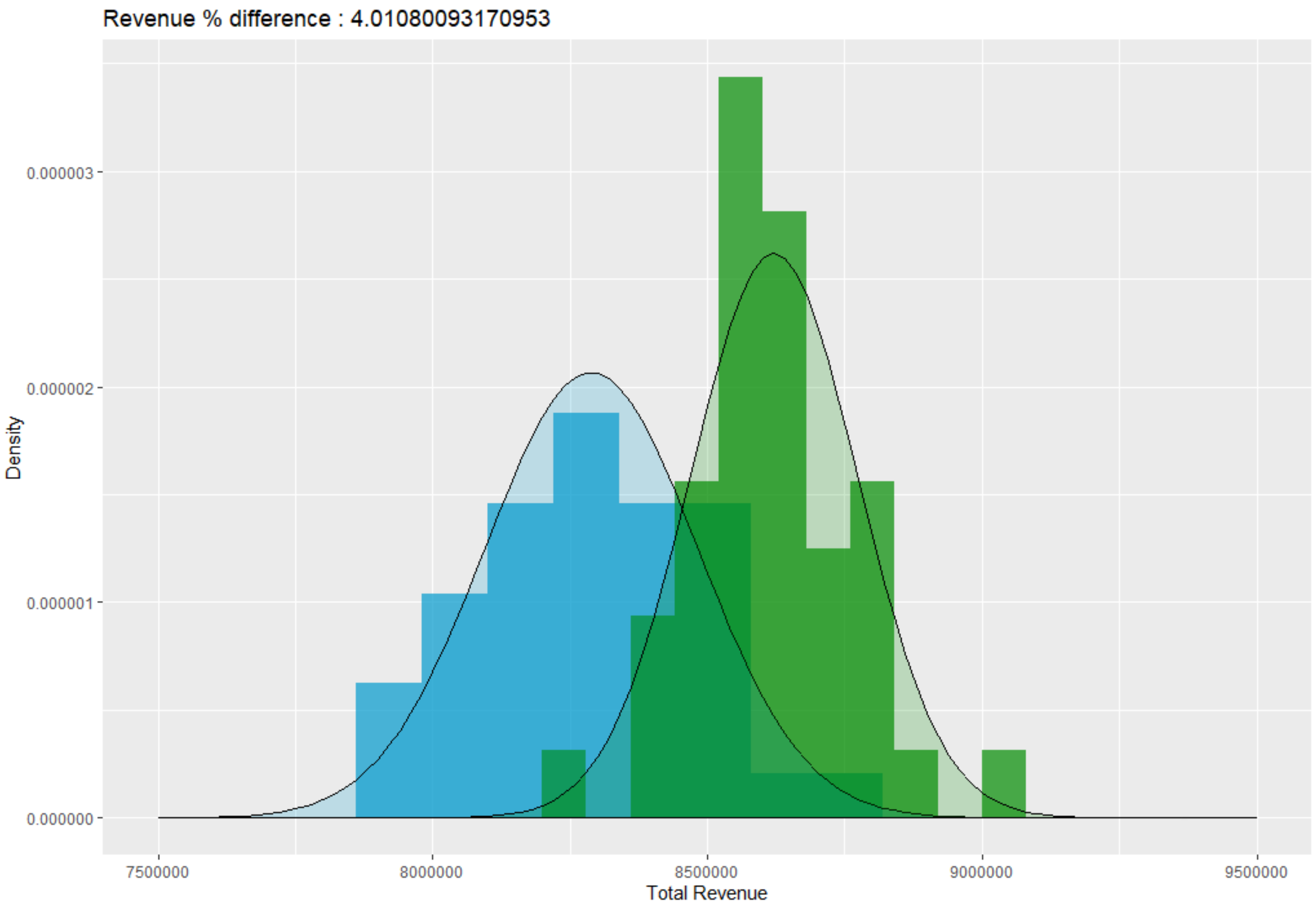
Comparison



t-test : 8.54, p-value ~ 0

Concluding remarks

-A good way to model complex systems

-Experimentation on interventions

-Programming with random numbers

Checks

-Classes

-Command/batch exec of R

-Stochastic = random – random variables over time

Thank you!

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