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PROFIT OF SCALPING

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ABSTRACT

In this project, we will study the revenue that could be generated from a scalper business, which is to send scalpers to long-waiting queues, and sell those earlier positions to the later comers. In order to calculate the revenue, we first simulated the queue with multiple parameters, like arrival rate, departure rate and total time that the queue is open for, and generated queue length. After that, we defined a formula for revenue, which includes a scalar, wage, time each scalper worked for and the position skipped by the customers who purchased from the scalpers, and studied the change in revenue in relation to queue length, the scalar, the number of scalpers sold to customers and the number of servers. Similar as expected, the total revenue has a positive correlation with the first three parameter, and has a negative correlation with the last one, number of servers, with some fluctuations.

1 INTRODUCTION

Nowadays, scalping has become a ubiquitous business for some popular events. Want to buy lunch from a famous restaurant? Wake up at 5 am and start lining up! Trying to watch a Duke University basketball match? Come and set up a tent one week prior to the match! Such painful waiting undoubtedly provides a good environment for scalping business, and it is intriguing to see the potential value of it. Nowadays even online shopping can be involved with scalping. Whenever some limited Nike shoes got released, they can be sold out in less than 1 minute, and people have to even draw lots to be eligible to throw their money away. Since scalping, though exists all over the world, had always been considered as a not so serious business and not a real 'job', it would be interesting to learn more about scalping and seek ways to maximize its attractiveness.

In this project, our team will assume that if there would be a start up company, whose main business is scalping on the queuing position, which is to send scalpers to the locations with is a long queue waiting to get served, like the line up for the Duke University basketball match, and sell the earlier positions to people who arrive later with certain prices. In particular, the project will use simulated data to generate a M/M/C queue with several traits of input parameters to first examine the behavior of the queuing system. Then scalpers were set to join in the queue whenever a criteria is fulfilled, in this case, when the queue length reaches a predetermined value **k**. For each incoming customer, he/she is associated with a variable, indicating the willingness of this customer to spend money in exchange of some positions ahead. The system was then constructed with customers coming and swapping with scalpers at some certain rate. Consequently, the main focus of this project is to investigate how the company can maximize profit, and the relationship between queue length and total profit (revenue minus cost).

In order to study this topic, we focus on two aspects of the project - the queue and the pricing strategy. For the queue, we simulated the queue length under different arrival rate, service rate, number of servers and the total time that the queue is open, with the detailed assumptions and methodology described in the

"SIMULATION OF THE SYSTEM" section below. For the pricing strategy, we calculated the total profit under different queue length, with the detailed assumptions and methodology described in the "PRICING STRATEGY" section below.

2 SIMULATION OF THE SYSTEM

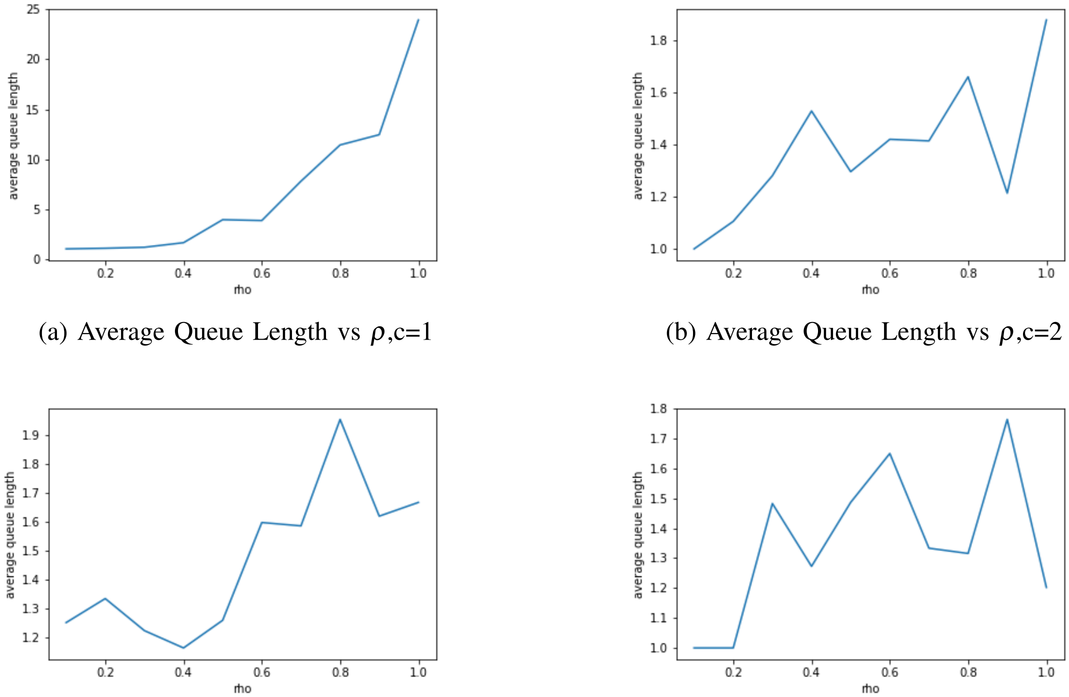
In order to estimate the revenue that the company would generate, we need to first understand the queue. For simplicity, both the arrival rate λ and the service rate μ in this model were assumed to be exponentially distributed. To simulate the queuing system, a few parameter for the object needs to be determined, which are arrival rate λ, service rate μ, number of servers **c**, and time length **T**, which denotes the total time within our study.

There were two types of arrivals to be generated. The first one is ordinary customers, who may or may not had the desire to spend money to save some time in waiting. The logistics of simulating this type of arrivals was to generate a sequence of inter-arrival times, with the cumulative sum as each customer's exact arrival time. In order to compute the departure time, service times were generated, again using exponential random variables. However, this time it was necessary to consider whether the time a customer starts to receive service is the same as his/her arrival time, since it is possible that one comes before any server is available. As a result, the departure time of the customers were computed as

$$max\{arrival\ time, min\{departure\ time\ of\ customers\ being\ served\}\}$$

The *min* part represents the earliest time when customers, who are being served, leaves; and the *max* part means that, the time when an incoming customer can get service is the later among the term just described and the customer's arrival time.
The second type of arrivals is the scalpers. Unlike the ordinary customers, the scalpers don't come in exponential inter-arrival times, but instead join in the queue instantaneously whenever the queue is long enough. In order to simulate the scalpers, the queue length was always recorded and updated whenever a customer arrives. Once the queue length reaches the predetermined value **k**, the scalper was inserted with the same arrival time as the previous customer. The service time of the scalpers was set to 0, because it was assumed that scalpers themselves wouldn't get the service but leave immediately when it was his/her turn.

Below, as shown in Figure 1, is a sample plot made by fixing the values **p**=0.2 (definition of p is in the next paragraph) and **k**=3 with number of servers **c**=1,2,5,and 10 respectively (we started from a M/M/1 queue with c = 1, then generalized it to be a M/M/c queue with c = 2/5/10), and average queue length was calculated against different values of ρ (which is λ/μ, and we decided to use ρ as the independent variable because the queue length of both M/M/1 and the M/M/c queue are dependent on ρ). From the chart, we found that generally speaking, the queue length increases as ρ increases, but when number of server c gets larger (c = 5 or 10), the trend fluctuates stronger, and for c = 10, the increasing trend becomes vague.



(a) Average Queue Length vs ρ,c=1

(b) Average Queue Length vs ρ,c=2

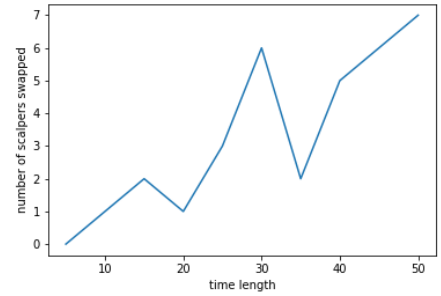
(c) Average Queue Length vs ρ,c=5

(d) Average Queue Length vs ρ,c=10

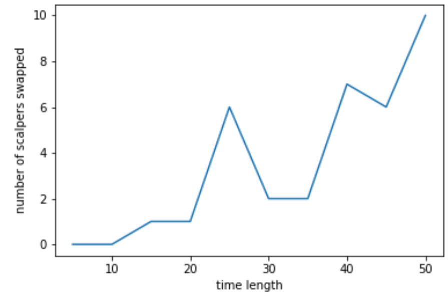
Figure 1: Average Queue Length vs ρ and different c

After having the system with customers and scalpers, the task was to find out the way to implement the behavior of purchasing the position from the scalper. And the idea was to generate a boolean variable, which had probability **p** to be True. For every incoming ordinary customer, he/she was associated with one of this boolean variable. On the other hand, the scalpers didn't need this boolean variable and were instead bear with a label 'scalper'. Thus, if the boolean value for a customer was True, we traverse through the queue to see whether there is any element in the line with the label 'scalper'. If so, their indices would be swapped, and the scalper get removed from the list because the job was finished.

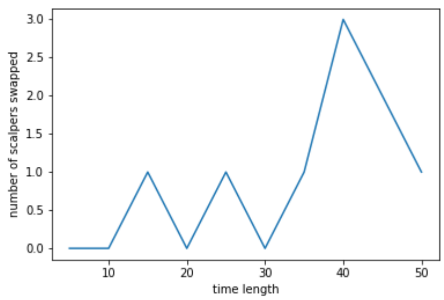
Below, as shown in Figure 2, is the plot of number of scalpers when changing time length T (the total time that the queue is open for). Similar as the figure above, we started from M/M/1 queue (c = 1), and generalized it to be M/M/c queue (c = 2/5/10). From the figure, we can easily see that the number of scalpers sold their position to a customer is increasing when the time length gets larger, in general. However, when c gets larger, the line fluctuates stronger. Furthermore, the more servers there are (c gets larger), the less people purchase from scalpers, in general, with an exception for c = 2.



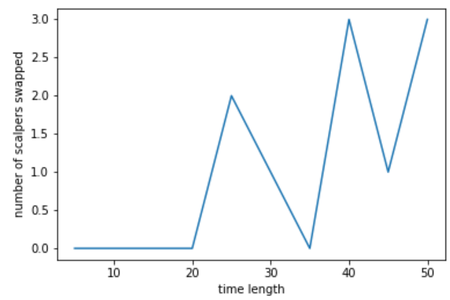
(a) Number of Scalpers Purchased vs Time Length T, c=1



(b) Number of Scalpers Purchased vs Time Length T, c=2



(c) Number of Scalpers Purchased vs Time Length T, c=5



(d) Number of Scalpers Purchased vs Time Length T, c=10

Figure 2: Number of Scalpers Purchased vs Time Length T, with different c

3 PRICING STRATEGY

After simulating the queue, we started to discuss the profit that can be generated from this scalping business, and would like to show the profit visually so that it is easy to find the best or most efficient parameters to max profit.

When talking about profit, we need to looking at two sides - revenue and cost. We start from the easier one, cost. For simplicity, we are only considering the variable cost generated by this scalping process, which is the labour cost - the wage that we need to pay to the scalpers. We are ignoring the other costs like rental and utility for the office, because disregard what pricing strategy we would like to utilize, these are the non-changeable costs that needs to be subtracted from total profit, so they are like a offset which does not impact the trend of profit, so we ignore them to reduce the complexity of the strategy. We decided to pay for the scalpers based on their time spent on waiting in the queue, and since this position requires little training and technical skills, we decided to pay the scalpers based on minimum wage. The minimum wage for different countries and different states are different, but since we would like to apply this model in the US, and cross states, we decided to use the minimum wage for the US as a whole, which is $7.25 per hour, so the total cost for hiring the scalpers are the sum of each individual's working time in hours (time spent waiting in the queue) multiplies the wage, which is $7.25.

For the second aspect, which is revenue, which is also the price we would like to charge on each purchase from scalpers, we believe it is related to the cost, because if the wage to scalpers is high, we need to set the price high to make of it. And the revenue is also related to the position skipped by the person who purchased the scalper's position, to be specific, if our scalper is the fourth person in the queue, and a new person arrives at position 20, and he/she would like to purchase the position from the scalper, then the position he/she skipped is 20 - 4 + 1 = 17. The reason why we think the position skipped is important is because, the more positions skipped, intuitively speaking, the more time saved from lining up, and the more we would like to charge this transaction. Given these reasoning, we finalized the logic for revenue. The revenue for each transaction on position is proportional to the multiplication of wage ($7.25 per hour as mentioned above), working time for each scalper (in hour) and the position skipped by this purchase (the difference between the position of the customer and the scalper), so the total revenue is the sum over all of the scalpers who sold their positions to a customer, the multiplication of wage, working item, position skipped, and a scalar α, and we will plot the chart with different α, and identify the impact of α to total profit, which is the difference between revenue and cost.

The mathematical form of the pricing strategy (or the profit) and its parameters are as follows:

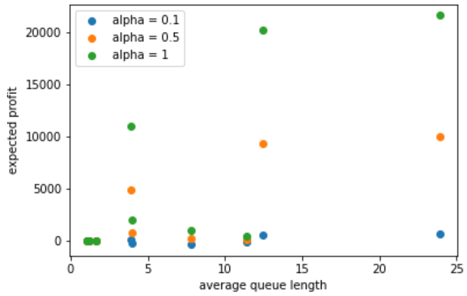
$$\begin{aligned} profit &= revenue - cost \\ &= \sum_{i=1, i \in swapped\,scalpers}^{n} \alpha w t_i \Delta k - \sum_{i=1}^{n} w t_i \end{aligned}$$

Where:

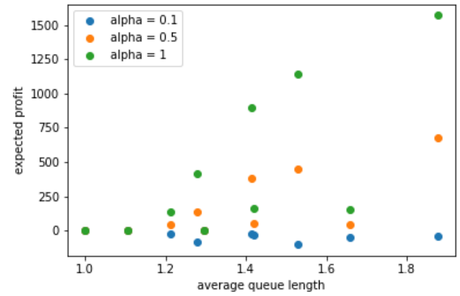
n: total number of scalpers (disregard whether sold the position)
α: scalar
w: hourly wage ($7.25 per hour)
t_i: working hours of each scalper (leaving time subtracting arrival time for each scalper)
Δk: position skipped for each customer who purchased scalper's position (position of the purchased customer subtracting the position of the scalpar)

After having these functions and parameters defined, we calculated the expected revenue as a function of the dependent variable for the 2 sets of plots above (average queue length and the number of scalpers sold their positions to customers), and the results are as in Figure 3 and Figure 4. For both of the sets of plots, with revenue as the dependent variable, we used scatter plots to show the total revenue when the scalar, alpha is taking 0.1 (blue), 0.5 (orange) and 1 (green).

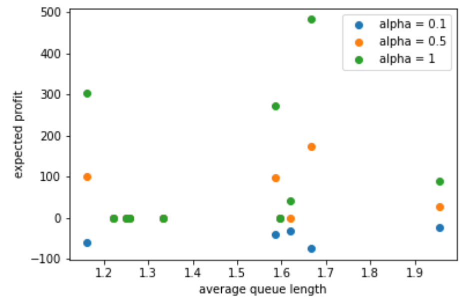
For Figure 3, Expected revenue vs Average Queue Length, it is clear that when as the alpha increases, the expected revenue goes up, which aligns with the formula above, the total revenue has a position correlation of the scalar alpha. Moreover, when the queue length increases and/or the number of server c decreases, the expected revenue increases, which intuitively explainable, as the queue length increase, more people would be willing to pay for an earlier position to save time; and as number of server increase, the longer the queue will be. However, as number of server gets larger, this increasing trend is not as clear, which is because the expected queue length is not changing enough (the difference between max queue length and min queue length is below 1 person), so the advantage of expected revenue in terms of queue length is not as strong.



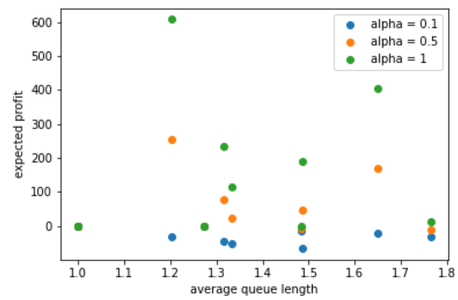
(a) Expected revenue vs Average Queue Length,c=1



(b) Expected revenue vs Average Queue Length,c=2



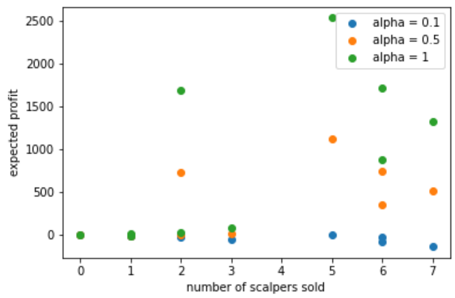
(c) Expected revenue vs Average Queue Length,c=5



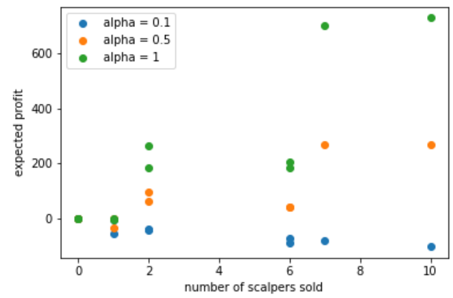
(d) Expected revenue vs Average Queue Length,c=10

Figure 3: Expected revenue vs Average Queue Length and different c

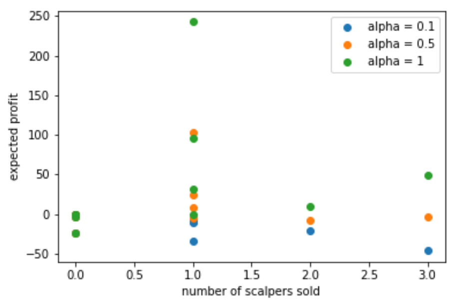
For Figure 4, Expected Revenue vs Number of Scalpers Purchased, Similarly as above, as the alpha increases, the expected revenue goes up, and when the number of server c increases, the expected revenue decreases. Furthermore, as number of scalper purchased (sold to customer), the expected revenue generally increase, but with great fluctuation, which is because that the position skipped is also an important factor on revenue calculation, and when the change in position is not as significant, the trend in revenue is not as strong, or may even move towards the opposite direction.



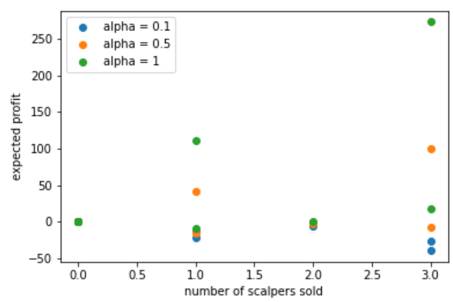
(a) Expected Revenue vs Number of Scalpers Purchased, c=1



(b) Expected Revenue vs Number of Scalpers Purchased, c=2



(c) Expected Revenue vs Number of Scalpers Purchased, c=5



(d) Expected Revenue vs Number of Scalpers Purchased, c=10

Figure 4: Expected Revenue vs Number of Scalpers Purchased, with different c

REFERENCES

AUTHOR BIOGRAPHIES

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