For office use only	Team Control Number	For office use only
T1 _____	**2020081**	F1 _____
T2 _____		F2 _____
T3 _____		F3 _____
T4 _____		F4 _____

2020

The International Mathematical Modeling Challenge (IM^2C) Summary Sheet

(Your team's summary should be included as the first page of your electronic submission.)

Flash sales at physical retail stores are getting more and more popular - in just one store, tens and hundreds of shoppers rush for discounts. While significantly increasing the sales of commodities, flash sale has also brought challenges to store managers. Among them, the damage of commodities is the major concern. In this paper, we aim to develop a quantitative model to help the store managers to design the optimal floor plan before flash sale and reduce damage cost.

To achieve it, we firstly build a **Popularity Evaluation model(PEM)** to rank the overall popularity of 134 flash sale products. In this model, we select 4 quantitative variables from the data provided and establish 3 evaluation indexes. Using linear weight methods, these three indexes are combined into a single one called Popularity index. The result shows that *wireless printer*, *27" IPS LED FHD FreeSync Monitor* and *Streaming 4K Ultra HD Audio Wi-Fi Built-In Blu-Ray Player* is the top three popular products and the whole ranking list is attached in our appendix.

Then we develop a **Damage prediction model(DPM)**. In this model, we consider three types of damages, which are damage at the original position, during transportation and damage near the entrance. For damage at the original position, we use Gaussian distribution to model the crowd density around the products and get its model parameter by S-curve. For damage during transportation, distance and size of the product are two major influencing factors, we use Manhattan Distance to model the distance between the flash sale item and the cashier, which is more suitable than normal distance. For damage near the entrance, we use the distance between products and entrance as the only one influencing factor and Manhattan Distance is also used.

Based on **PEM** and **DPM**, we develop a **Layout Optimization Model(LOM)**. To begin with, we fix the location of seven departments in the provided floor plan, and then we use Monte Carlo simulation to arrange the location of products within each department. We choose the best one out of 10000 results and the cost of damage in this layout is predicted to be **9314$**. After that, we also improve the design of the floor plan and rerun LOM. The result shows that in the newly designed layout, the cost of damage in this layout is predicted to be **8820$**, which is 5.3% less than the former layout, which means our new design indeed improves the overall performance.

Keywords: Gaussian distribution, Manhattan Distance, Monte Carlo simulation

Letter to manager

Dear Sir,

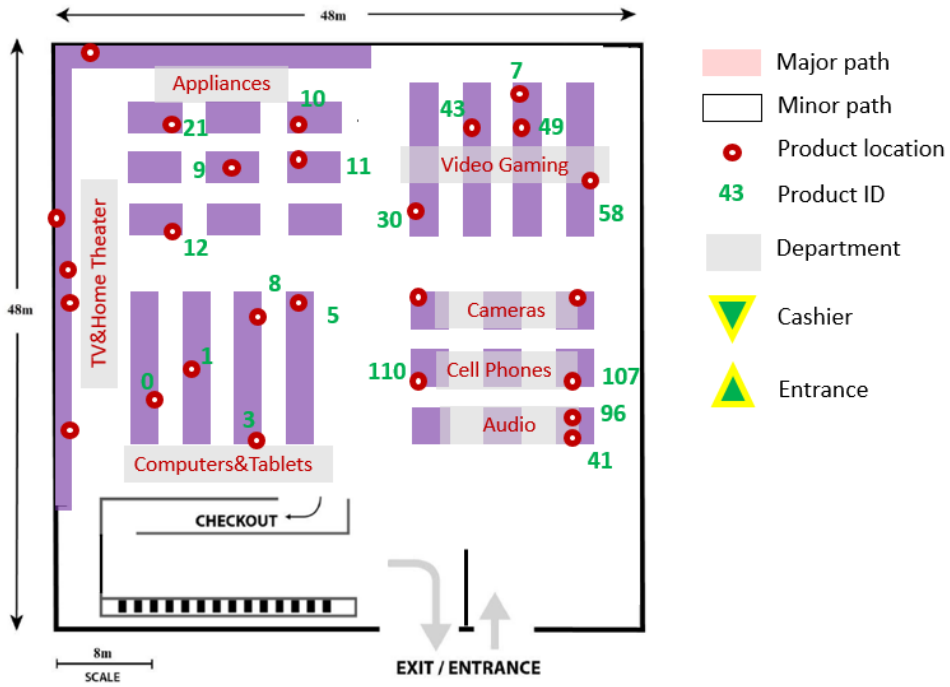
Thank you for giving us the opportunity to contribute to the upcoming flash sale event. Over the past few days, our team has worked out a new store floor plan with a layout of different departments and flash sale products for the purpose of minimizing the cost due to damages to the products.

In the process of designing the store layout, we have identified a few important factors. First, the popularity of each flash sale product which affects the density of customers around them. Second, the possible ways of damage. Third, a quantitative analysis of the customer's behavior. Addressing these factors is crucial to finding a well-round solution.

We evaluated the popularity of each one of the flash sale products based on the size of the discount, quantity available and customer ratings and ranked them against each other. Through analysis of a typical flash sale event, we have identified three ways in which a product can be damaged: damage at a product's original position, during transport to the cashier, and near the entrance/exit where customers rush in/out. In chaotic situations, the behaviors of the customers can be difficult to quantify. So, in order to quantitatively define the consequences of the customers' actions in the most accurate way possible, we first predicted the probabilities of damage at a popular product's original position, during transport, and near the entrance and exit. Very importantly, we can then estimate the damage cost based on the probabilities of damage. This gives us a clear picture of 'how much' damage there is.

With all of the factors readily available, we optimized the locations of the flash sale products using a Monte Carlo simulation program, which allowed us to find the optimal layout with the lowest cost possible. Additionally, we generated a brand new store floor plan by re-locating the departments and re-shaping the cashier. Using the simulation program on the new design, we found a new layout of the flash sale products that leads to a lower damage cost.

Attached is our new design of the store floor plan and the locations of the top-ranked flash sale products. Thank you again for your interest and we look forward to your feedback.



1 Introduction

1.1 Background

Flash sales at physical retail stores are getting more and more popular - in just one store, tens and hundreds of shoppers rush for discounts. During flash sales, the limited quantity of product causes irrational buying. As a promotional marketing strategy, flash sales are successful in allowing the store to make huge profits. At the same time, flash sales pose increased challenges for brick-and-mortar businesses. Whilst special pricing and discounts may attract many shoppers, dense crowds in physical retail could bring damages to the flash sale products, resulting in extra costs for the stores. Huge electronic devices with fragile screens such as TVs and monitors can be easily broken during transport from their shelves to the cashier.

Moreover, numerous cases of fighting over and damaging popular discounted products have been reported on the news[1]. From the perspectives of the merchants, we need to establish a deep insight into the ways we can arrange the departments and flash sale items in order to minimize damage due to stampede or mall fights. Thus, to address this problem, a quantifiable scheme that can be achieved through mathematical modeling proves to be essential.

1.2 Problem Restatement

In this modeling, we will address the following three problems:

1. According to the data provided, rank the popularity of 134 flash sale products and find the most popular ones.

2. Based on the current floor plan, develop a quantitative prediction model to help store managers to optimally arrange the location of discounted products, and estimate the resulting cost caused by the damage of commodities.

3. Adjust the current floor plan and get a better layout with less damage cost.

2 Assumptions and Variables

2.1 Assumptions

Assumption 1: Only four variables, *Regular/Suggested Retail Price (USD), Price During Flash Sale(USD), Quantity Available During Flash Sale, and Customer Rating (1-5)* affect the popularity of a flash sale item. The others such as *Make (Brand)* and *Major Product Category* have little impact on popularity.

Justification1: Text information is difficult to process. Plus, compared with discount, brand name or major product category have little or no effect on popularity, which we can ignore.

Assumption 2: When we evaluate the popularity of a flash sale product, we regard the size of the discount (percent-off) as the most important factor.

Justification2: It is the discounts that attract shoppers. Most shoppers go to flash sales seeking good bargains. The larger the discounts, the more popular an item might be. Customer rating and quantity available also has some effects on the popularity of a product.

Assumption 3: We assume that the flash sale products will only have three categories of damage: damage at the original site, during transport with collateral damage near the entrance and exit. These three damage is not connected nor correlated with each other.

Justification3: All these circumstances are independent and do not collide with each other, because all damages could happen on one product. So they can be added together.

Assumption 4: Assume the high density of customers is related to the products, and it follows the pattern of Gauss distribution. The peak of the distribution is mainly correlated with the popularity index.

Justification4: Gauss distribution is better than other distribution methods as it gives a heat-up of influence the product is causing.

Assumption 5: When calculating the distance between two points, we all use the Manhattan distance.

Justification5: Although the customer's walking path in the mall is difficult to predict, Manhattan distance is more representative of the customer's true path length in the mall than normal distance.

Assumption 6: In our Layout Optimization Model, we only consider the top five products from each department while ignoring the impact of the other products on the model.

Justification6: It is the most popular flash sale products that lead to human traffic-jams. Once we address the layout of these products, we can achieve the layout optimization for the lowest cost. The algorithm would be too complicated to be implemented if we attempt to place every single flash sale item on the store floor plan.

2.2 Variables and Description

Notations	Description
α_i	Discount index of the i^{th} product
Q_i	Quantity Available of the i^{th} product
R_i	Rating Index of the i^{th} product
P_i	Popularity index of the i^{th} product
p_i	Probability of damage
W_i	Price of the ith Item
C	Money lost due to damage
A_i	Probability of Damage at an item's original location
d_i^c	Manhattan Distance between the i^{th} product and the cashier
d_i^e	Manhattan distance between the i^{th} product and the entrance

3 Popularity Evaluation Model

In order to examine the desirability of the flash sales items, we build a **Popularity Evaluation Model (PEM)**. We choose four quantitative variables out of nine from the data provided, namely, *Regular/ Suggested Retail Price (USD), Price During Flash Sale(USD), Quantity Available During Flash Sale, and Customer Rating (1-5)*. We do not consider the other five text variables such as Make (Brand) and Major Product Category because they are difficult to process and we also know that brand influence is weakened during flash sale, most shoppers go to flash sales seeking for good bargains(which can be directly shown by the price). Using these four variables, we develop three indexes to evaluate the popularity of a product: discount index, quantity index and rating index. Next, we will explain three indexes in detail.

3.1 Discount Index

According to our life experience, the percent of discount is one of the most important indicators for measuring the popularity of goods during flash sales. The Discount Index can be calculated by

$$\alpha_i = \frac{S_i - S_i'}{S_i} \times 100\% \tag{3.1}$$

where S_i is the Regular/ Suggested Retail Price (USD) of the i^{th} product, and S_i' is the Price During Flash Sale (USD). Most consumers go to flash sales expecting to pick up good bargains. Hence, the bigger α_i is, the more popular an item can be.

In order to make different indexes comparable, we will normalize each one of them. For Discount Index, we use the Min-Max normalization method to mapping all the data to the range of $[0, 100]$:

$$\alpha_i^* = 100\frac{\alpha_i - \min\{\alpha_i\}}{\max\{\alpha_i\} - \min\{\alpha_i\}} \tag{3.2}$$

3.2 Quantity Index

We assume that a scarcity of an item during the flash sale can attract more customers. That is to say, under the same discount percent, the rarer the product, the more likely it is to cause panic buying and therefore more popular. So we simply use Quantity Available to be the Quantity Index.

Again, Min-Max normalization method was used to mapping the Quantity Index to the range of $[0, 100]$:

$$Q_i^* = 100\frac{\max\{Q_i\} - Q_i}{\max\{Q_i\} - \min\{Q_i\}} \tag{3.3}$$

where Q_i is the Quantity Available of the i^{th} product.

3.3 Rating Index

Products with higher customer rating must be more popular. Also, Min-Max normalization method was used to mapping the Rating Index to the range of $[0, 100]$:

$$R_i^* = 100\frac{R_i - \min\{R_i\}}{\max\{R_i\} - \min\{R_i\}} \tag{3.4}$$

where R_i is the customer rating of the i^{th} product.

3.4 Popularity Index

We use a linear weighting method to combine the three indexes mentioned earlier into one - the popularity index:

$$P_i = w_1\alpha_i^* + w_2Q_i^* + w_3R_i^* \tag{3.5}$$

In which α_i^*, Q_i^*, R_i^* are the normalized value of the three indexes, and w_1, w_2, w_3 are the relative weights of the three indexes, in our model, we use $[w_1, w_2, w_3] = [0.6, 0.2, 0.2]$.

3.5 Results and Analysis

Implementing the algorithms above in *Excel*, we obtain the top ten most popular items, results are shown in Table 3.1. The complete ranking list is attached in the appendix.

Since in the Popularity Evaluation Model, we regard the size of the discount as the most important factor, the top ten popular products basicly have the largest discounts amongst all. For instance, the most popular flash sale product, Wireless All-in-One Printer, has the largest discount. At the same time, the least popular product, 70" 4K UHD HDR Smart LED TV, 6 Series, has the smallest discount. It also comes in a large quantity and has a relatively low customer rating, which contributes to its low ranking. Figure 3.1 is the histogram of their popularity index. We can see

from Figure 3.1 that the distribution curve of popularity index is close to the normal distribution, which means that the distribution of most products fall in the middle level, and low and high scores are relatively rare. Hence, our popularity evaluation model is proved to be reasonable and distinguishable.

Table 3.1: Top 10 Most Popular Products

Product	**Popularity Index**	Percent Off	Quantity	Customer Rating
Wireless All-in-One Printer	**79.15**	71.44	12	4.1
27" IPS LED FHD FreeSync Monitor	**76.03**	56.00	12	4.8
Streaming 4K Ultra HD Audio Wi-Fi Built-In Blu-Ray Player	**73.09**	50.00	8	4.7
Streaming 4K Ultra HD Hi-Res Audio Wi-Fi Built-In Blu-Ray Player	**72.83**	48.00	8	4.8
11.6" Chromebook, Intel Atom x5	**72.17**	52.91	10	4.6
4K Ultra HD Blu-Ray Player	**71.56**	50.00	8	4.6
Wireless All-in-One Instant Ink Ready Printer	**71.02**	55.56	12	4.5
15.6" Gaming Laptop, AMD Ryzen 5	**70.08**	43.75	10	5
31.5" IPS LED FHD Monitor	**67.56**	50.00	12	4.6
5.3cu ft Slide-In Electric Range	**66.61**	41.18	5	4.6

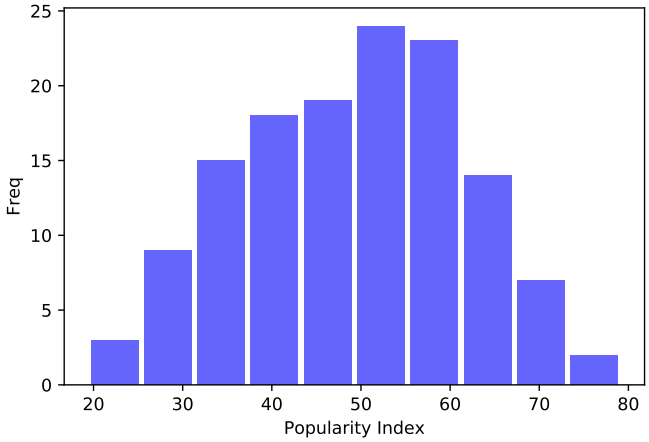


Figure 3.1: Result of Popularity Evaluation Model

4 Damage Prediction Model

We assume that during the flash sale, the most important form of loss is damage to the products. Damage to shelves, floors, shopping carts, etc. rarely occurs and can be ignored. Through our analysis, we identify three types of product damage during flash sale (see Figure 4.1):

1. **Damage at original position**. During the flash sale, people will gather near popular products, and the resulting high crowd density will inevitably cause damage. Typical damages of this type include packaging failure caused by intense panic buying and the falling of product for those near the major pathway. This type of damage depends largely on the arrangement of the department and the layout within each department. To reduce this type of damage, popular products need to be dispersed rather than aggregated. Also, popular products need to be placed away from the major pathway to prevent congestion.

2. **Damage during transportation**. From our Popularity Evaluation Model, large appliances, TVs, and computers are the most popular products. However, such products are often bulky and easily damaged during transportation. Obviously, this type of damage is closely related to the size of the products and the distance from the cashier to where they are placed.

3. **Damage near the entrance**. When the flash sale starts, many crazy customers will rush into the mall from the entrance, which may cause damage to nearby products. This type of damage is closely related to the distance from the entrance to where the products are placed.

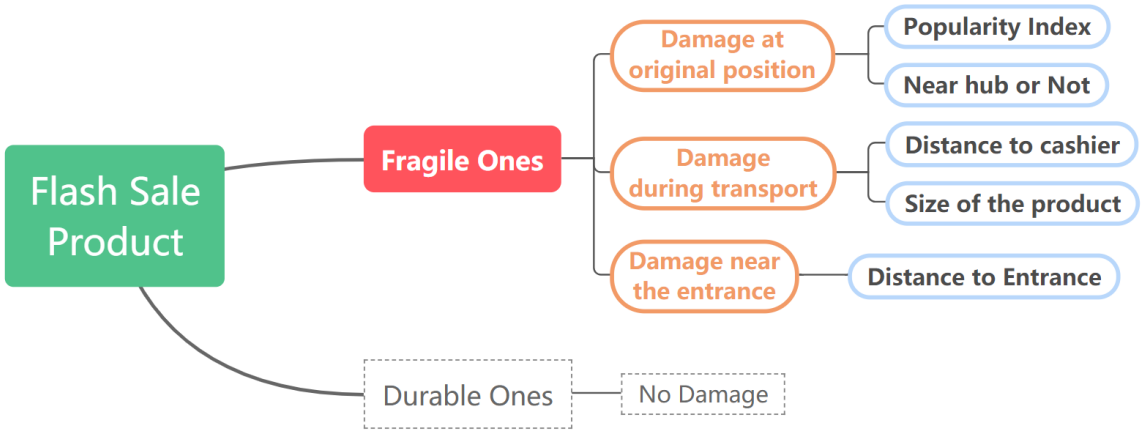


Figure 4.1: Three types of damage

Whether the flash sale product will be damaged is closely related to its characteristics. Durable items such as phones and earplugs can endure a lot of hits and bumps. However, televisions are more easily damaged due to their fragile screens. Big appliances are likely to be damaged because they are difficult to carry. Thus, we divide all flash sale products into two categories - those that are easily damaged and those that are not. We construct a Damage Prediction Model that concerns products that are easily damaged only. For robust items, we assume their probability of damage is zero.

We use probability method to model the damage of the flash sale items. The probabilities of the three types of damages for the i^{th} product are $p_i^{(1)}, p_i^{(2)}, p_i^{(3)}$ relatively.

The money lost due to damage on the i^{th} item can be calculated by

$$C = \sum_i p_i W_i Q_i = \sum_i \left(p_i^{(1)} + p_i^{(2)} + p_i^{(3)} \right) W_i Q_i \tag{4.1}$$

in which W_i is the price of the i^{th} item and Q_i the quantity available at the flash sale for the item. In the next few sections, we will model the probability of each type of damage.

4.1 Probability of damage at original position

We consider using the Gaussian distribution [2] to describe the crowd density near the product.

$$f_i(x, y) = A_i \exp\left(-\frac{(x - x_i)^2 + (y - y_i)^2}{2\sigma^2} \right) \tag{4.2}$$

In which, A_i is the maximum crowd density of the i^{th} product at its original position. (x_i, y_i) is the coordinates of the i^{th} product, and σ measures the influence decay rate of the product. Figure 4.2 is a typical Gaussian distribution diagram.

First, maximum crowd density (A_i) is related to its popularity index (P_i). The more popular a product is, the greater the number of customers want to buy it. So, damage may be caused by congestion and when customers are fighting over the product. In addition, we know that there is a high density of customers near the main paths of the store. Thus, the probability of damage is likely to be higher at these critical locations.

According to the above discussion, the relationship between A_i, P_i and major pathway or not, could be formulated by the following s-shape curve [3]:

$$A_i = \frac{K_1 K_2 e^{rP_i}}{K_2 + K_1 (e^{rP_i} - 1)} \tag{4.3}$$

in which P_i is the popularity index of the flash sale item, K_1 the initial value, and K_2 the final value, and r measures the rate at which the curve is changing.

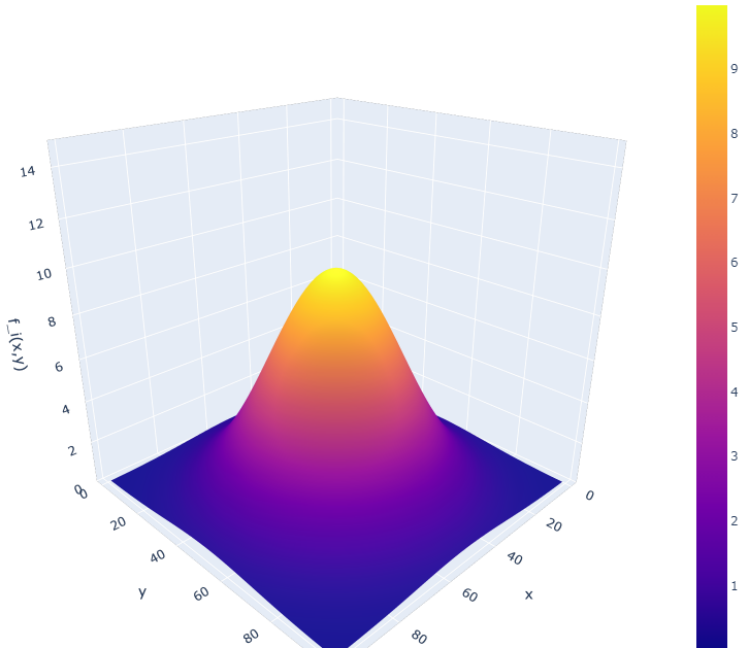


Figure 4.2: Gaussian distribution of damage probability

For major and minor pathways, we can put in different value for K_1 and K_2 and r (see Table 4.1). It can be seen from Figure 4.3 that due to the different values of K_1, K_2 and r, the probability of damage on the major pathway has always been greater than the minor pathway, and in both cases, A_i increases with increasing P_i.

Table 4.1: Parameter configuration table of A_i

Position	K_1	K_2	r
Major Path	0.05	0.3	0.1
Minor Path	0.01	0.2	0.06

Products will affect each other, so the density of people at any location should be equal to the superposition of the impact of all products, therefore,

$$p_i^{(1)} = \sum_{i=1}^{N} f_i(x,y) = \sum_{i=1}^{N} A_i \exp\left(-\frac{(x-x_i)^2 + (y-y_i)^2}{2\sigma^2}\right) \tag{4.4}$$

Where N is the number of products, in this problem, $N = 134$.

Through our method above, we can calculate the damage possibility of each individual product at its original site, known as $p_i^{(1)}$.

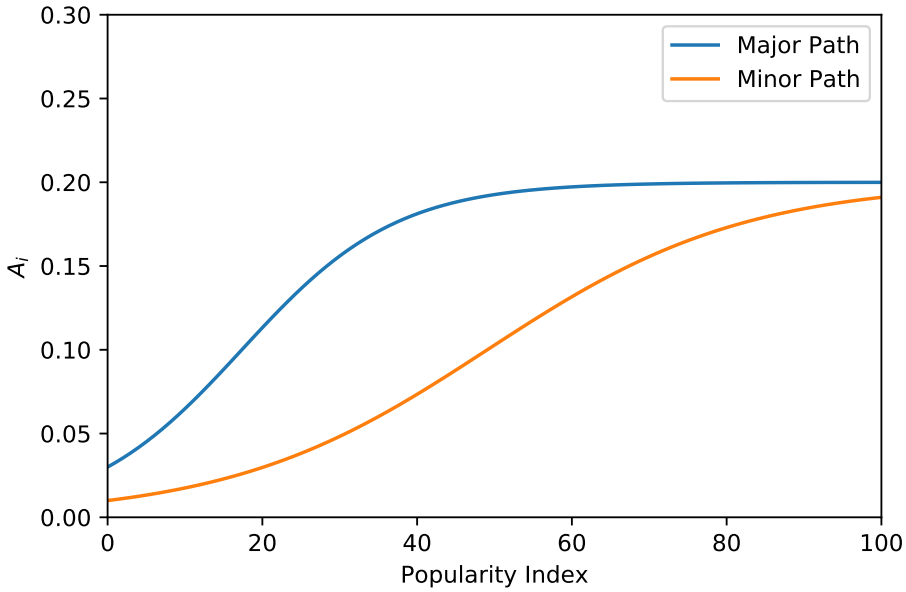


Figure 4.3: S-Curve of A_i for Product in major and minor pathway

4.2 Probability of damage during transportation

Damage could also happen during transportation, and this kind of damage relies on the size of the product and its distance to the cashier. Firstly, we consider using the Manhattan distance [4] to describe the product's transportation distance:

$$d_i^c = |x_i - x_c| + |y_i - y_c| \tag{4.5}$$

in which, d_i^c is the Manhattan distance from its original location to cashier of the i^{th} product. (x_i, y_i) is the coordinate of the i^{th} product, and (x_c, y_c) is the coordinate of the cashier.

Although the customer's walking path in the mall is difficult to predict, from Figure 4.4 we can see that Manhattan distance is more representative of the customer's true path length in the mall than normal distance.

In order to take the size of product into consideration, we develop the following equation to

combine the influence of size and distance:

$$p_i^{(2)} = s_i \frac{d_i^c}{\max\{d_i^c\}} \tag{4.6}$$

where d_i^c is the Manhattan distance from its location to cashier of the i^{th} product calculated by Eq.(4.5). We normalize it by dividing by the maximum value of $\max\{d_i^c\}$. s_i is size parameter, for simplicity, in our model, the size of products is divided into three categories: large, medium and small. Their corresponding s_i is shown in Table 4.2.

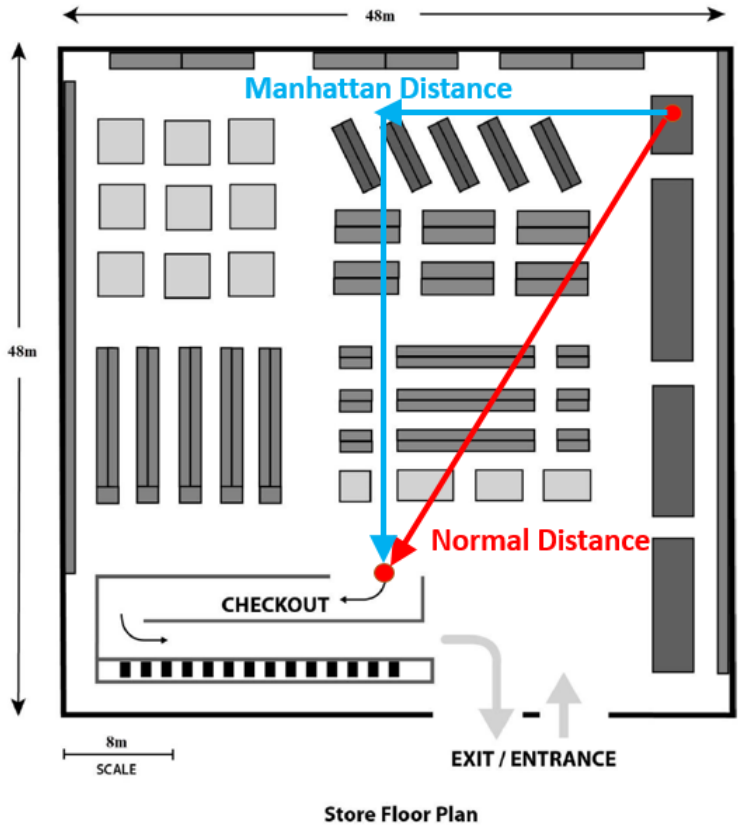


Figure 4.4: Comparison between Manhattan Distance and Normal distance

Table 4.2: s_i for different product size

Product Size	Large	Medium	Small
s_i	0.09	0.06	0.03

4.3 Probability of damage near the entrance and exit

There is usually a stampede of shoppers entering the store at flash sales. Hence, flash sale items near the entrance are more likely to get knocked over. The closer to the entrance an item is, the higher the probability of its damage. Again, we use Manhattan Distance to model the distance between the flash sale item and the entrance, which is given by

$$d_i^e = |x_i - x_e| + |y_i - y_e| \tag{4.7}$$

in which (x_i, y_i) are the coordinates of the i^{th} flash sale product and (x_e, y_e) is the coordinates of the entrance.

We model the probability of damage near the entrance by exponential function:

$$p_i^{(3)} = \exp\left(-k_e d_i^e\right) \tag{4.8}$$

The probability of damage is 1 when the flash sale item is at the entrance exactly (products are exposed to huge crowds), whilst the probability tends to zero as the distance from the entrance increases. So, we use of exponential function to model the probability of damage near entrance is reasonable.

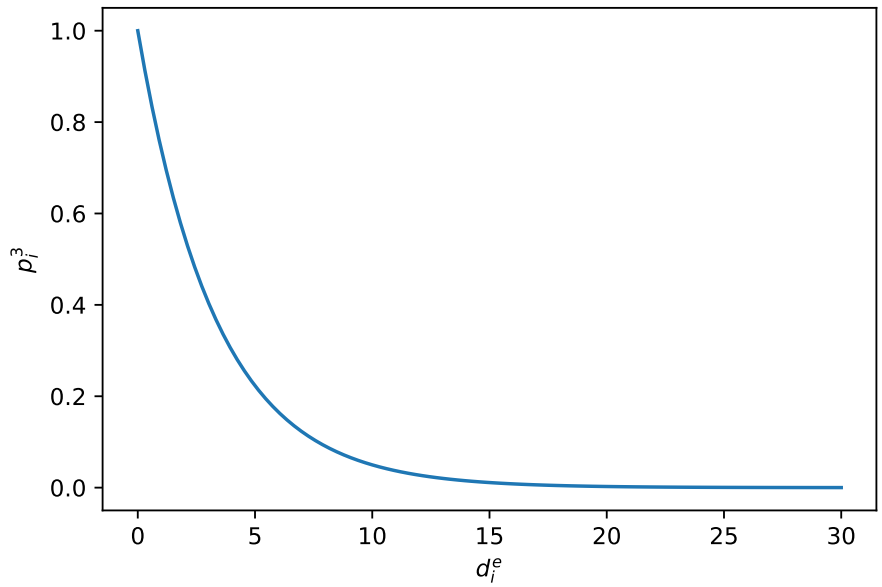


Figure 4.5: The probability of damage near the entrance modeled by exponential graph

5 Layout Optimization Model

5.1 Structure of Our Model

In order to determine the optimal locations of the flash sale products, we set up a layout optimization model based on the Monte Carlo simulation method [5]. In our model, the optimization variables are the locations of the flash sale products as presented in coordinates $(x_i, y_i), i = 1, 2, \cdots m$. The optimization objective is to minimize the cost due to damage of the products. We have discussed the equation for the cost (USD) in the damage prediction model, which can have been formulated by Eq.(4.1).

It is very difficult for us to arrange the layout for all the 134 products. Therefore, we consider fixing the location of the department first and then optimize the arrangement of the top 5 products inside the department. For this reason, we first designed the location of seven departments based on our life experience, the result is shown in Figure 5.1.

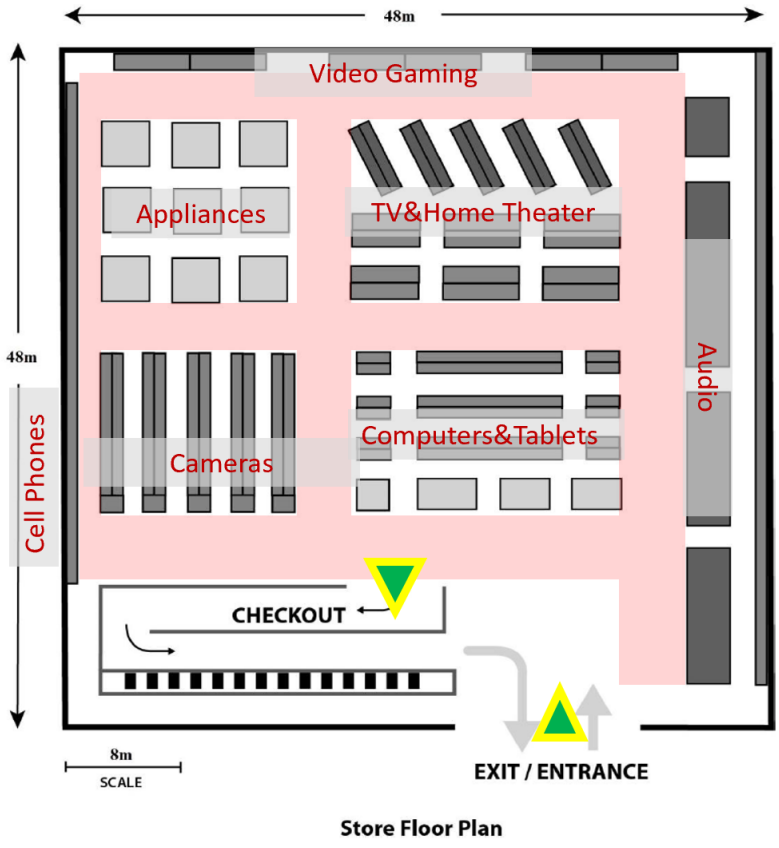


Figure 5.1: Department Locations and Major Paths

Each time when the Monte Carlo simulation is run, depending on the locations of the departments that we have decided earlier, we randomly place the top 5 flash sale products within their departments. These flash sale products cannot be placed unless they satisfy the restricted condition, that is to say, the products can only be placed on the shelves but not the pathways. Then we calculate and record the cost for each simulation. After the Monte Carlo program is run M times, we choose the simulation with the lowest cost and its corresponding flash sale item layout as the optimal layout. According to the theory of Monte Carlo simulation, the larger M is, the more likely our design will get better, but it is also more computationally intensive. In our model, We make a trade-off between accuracy and calculation time and choose $M = 10000$. Figure 5.2 further explains our calculation process.

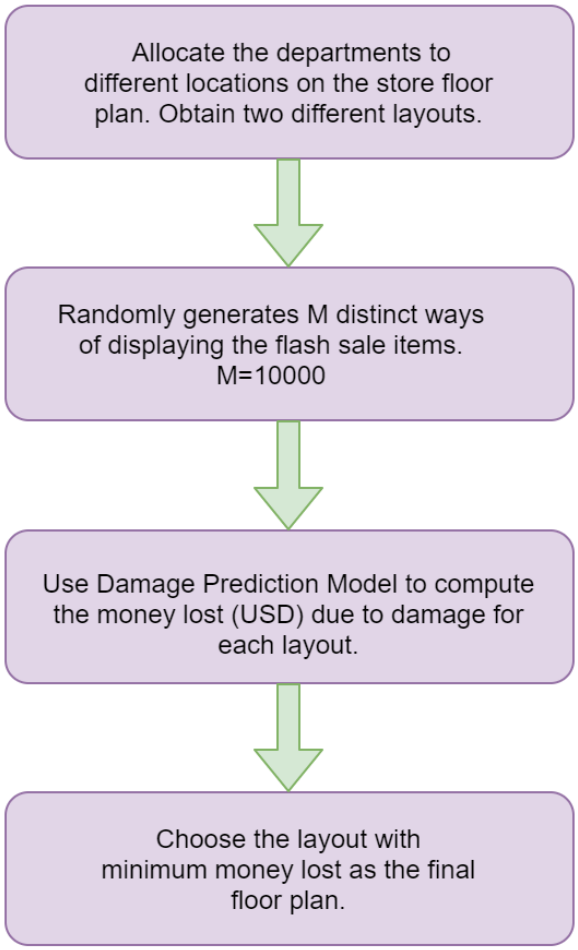


Figure 5.2: Flowchart of Our Model

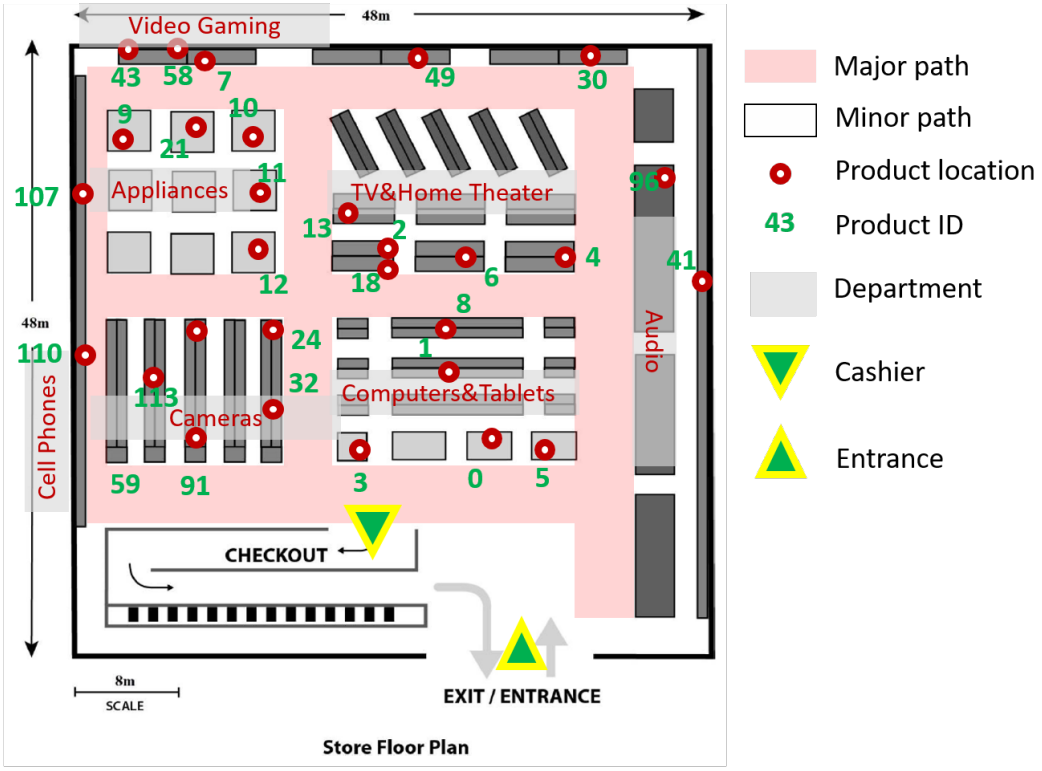
5.2 Result of Our Model

The optimal layout obtained by our Layout Optimization Model is shown in Figure 5.3. We find the layout with a damage cost of **$9314**, which is the lowest so far.

In Figure 5.3, the left figure is the detailed floor layout plan, with each red spot represents a product. The product ID is also labeled in this graph (since the name of the product is too long to insert into the layout plan, so we just label the points with numerical IDs, their relationship will be attached in our appendix). The right figure is a heat-map of damage probability, the brightest spots on the graph are areas with the densest crowds, which means that it is where the probability of damage is the highest. However, the bright spots are spread out on the graph which means that our layout plan is unlikely to cause large-scale congestion, thus helping to reduce damage and the corresponding cost.

Advantages of our Monte Carlo simulation program is straightforward: it randomly generates locations for the flash sale products, and we choose the layout with minimal cost. Its calculation is easy to understand and easy to program.

However, in Monte Carlo simulations, the locations of the flash sale products will differ from run to run due to randomness(We have avoided this phenomenon by specifying random seeds in Python this time). Also, Monte Carlo simulations can only allow us to find the relatively superior layout instead of the perfect layout.



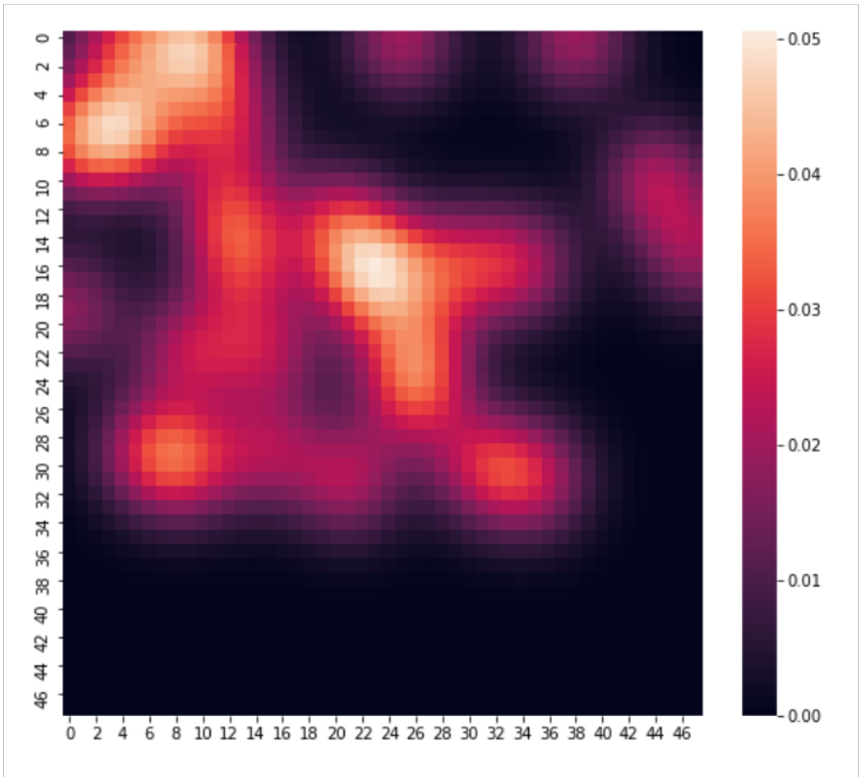


Figure 5.3: Simulation results of the optimization of the layout of flash sale products

6 New Layout Optimization Model

In the previous model, we analyzed the optimal layout under the original floor plan. In fact, we can also adjust the floor plan to get a better layout.

Firstly, we rank seven departments by their average popularity index. Since Computer Tablets is the most popular department, and their items are mostly fragile, we locate it just besides the cashier to avoid long distance transportation. For TV Home Theater, the space near the wall is more suitable. Appliances and Video Gaming have medium popularity, so we locate them in two corners of the mall. The other three departments, which are Cameras, Cell phones and Audio, have relatively small demand for space and are not very popular, so we merge them together and place them near the entrance. The adjusted floor plan is shown in Figure 6.1.

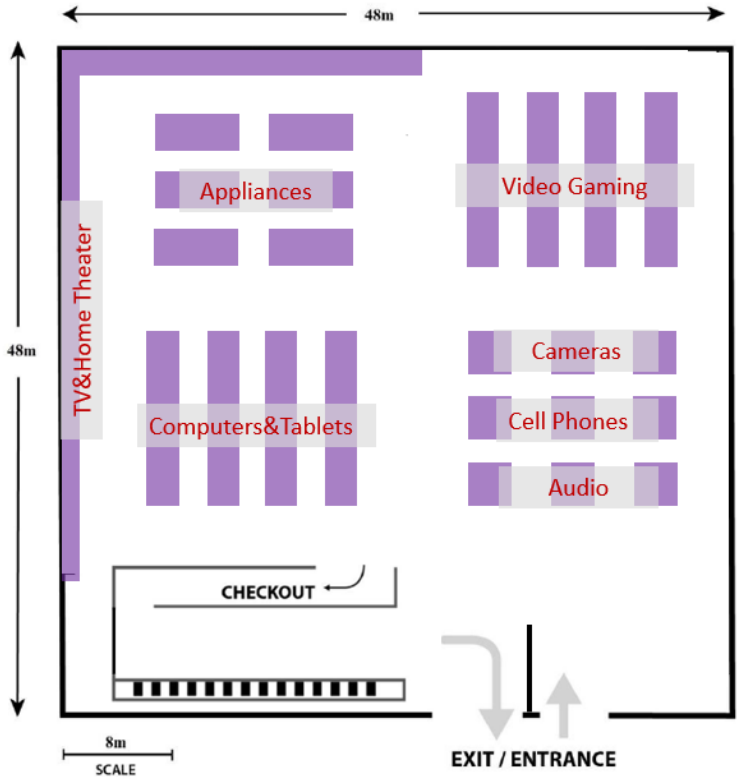


Figure 6.1: Map of new distribution of stores

Again, based on the newly designed floor plan, we performed the Monte Carlo Simulation on it and get the recommended layout, result is shown in Figure 6.2.

We can see very clearly from Figure 6.2 that after we have changed of layout of the stores, the

bright heat spots have been relocated and dispersed smoothly on the graph. It has efficiently cut the flow of customers and greatly decreased the rate of damage. New price of damage and lost has been allocated and the stores now are paying less to **$8820** rather than $9314.

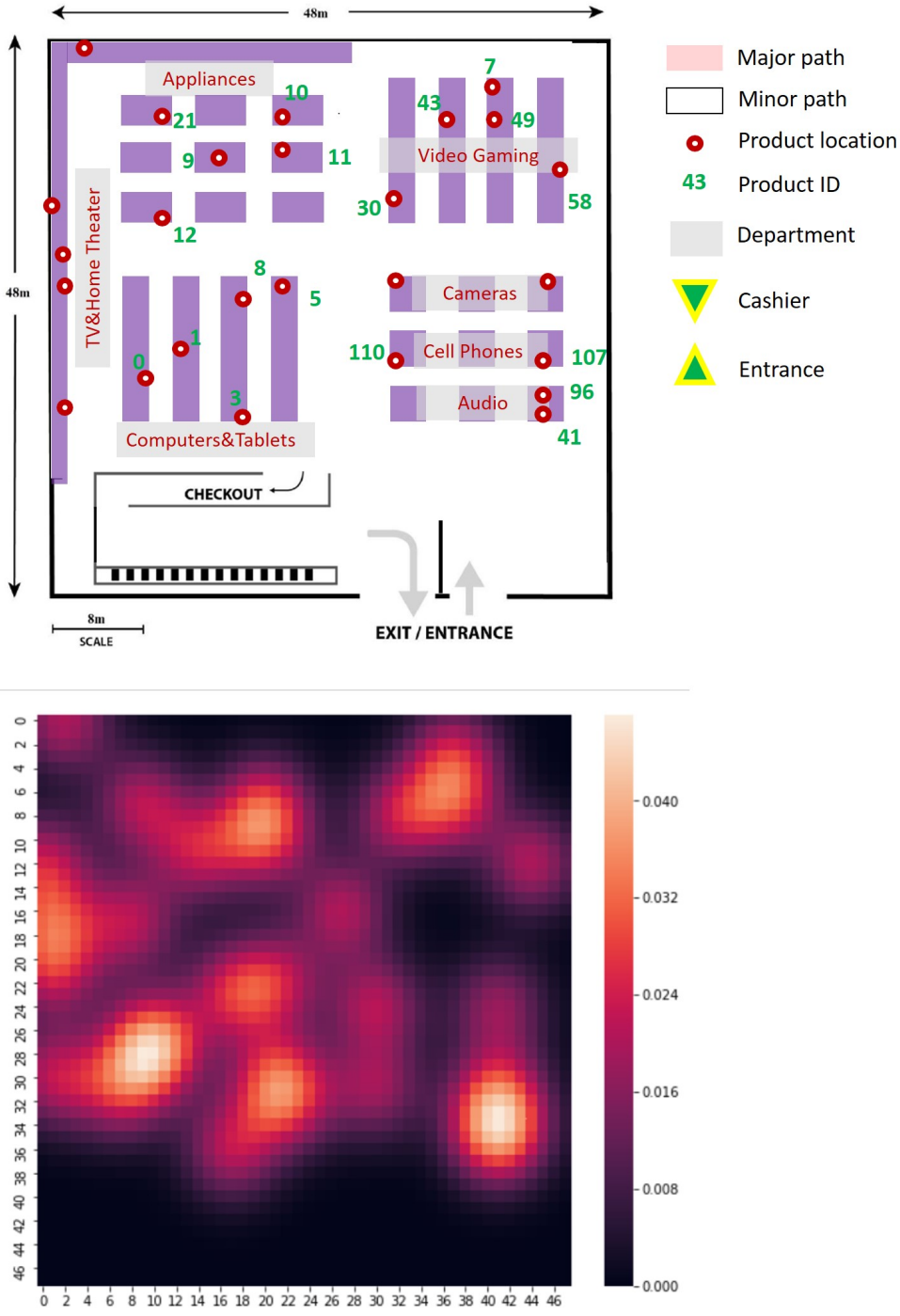


Figure 6.2: Map of the best distribution of stores after changing $8820

References

[1] Avoiding and Overcoming Flash Sale Failures. https://www.nchannel.com/blog/overcoming-flash-sales-failures/

[2] Wikipedia contributors. "Normal distribution." Wikipedia, The Free Encyclopedia. Wikipedia, The Free Encyclopedia, 9 Apr. 2020. Web. 18 Apr. 2020.

[3] Wikipedia contributors. "Sigmoid function." Wikipedia, The Free Encyclopedia. Wikipedia, The Free Encyclopedia, 6 Apr. 2020. Web. 23 Apr. 2020

[4] What is Manhattan Distance? ,Johnny Ho, https://www.quora.com/What-is-Manhattan-Distance

[5] An Overview of Monte Carlo Methods, Christopher Pease, https://towardsdatascience.com/an-overview-of-monte-carlo-methods-675384eb1694

Appendix

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
from mpl_toolkits.mplot3d import Axes3D
np.random.seed(0)

def gassian_distribution(x0,y0,A,density):
    sigma = 3
    for i in range(len(density)):
        for j in range(len(density)):
            density[i][j] += A * np.exp(-((i-x0)**2 + (j-y0)**2)/2/sigma**2)
    return density



def A(p,k1=0.03,k2=0.2,r=0.1):
    return 0.1*(k1*k2*np.exp(r*p))/(k2+k1*(np.exp(r*p)-1))
```

```
def p1(locationdata):
    density = np.zeros((48,48))
    for i in range(len(locationdata)):

        density = gassian_distribution(locationdata['loc'][i][0],
                                       locationdata['loc'][i][1],
                                       A(locationdata['Popularity Index'][i]),
                                       density)
    d_list = []
    for i in range(len(locationdata)):
        d_list.append(density[locationdata['loc'][i][0]][locationdata['loc'][i][1]])
    return d_list,density



def p2(locationdata):
    cashier = (48 - 11.5,22.5)
    d_list = []
    for i in range(len(locationdata)):
        d = abs(locationdata['loc'][i][0] -cashier[0]) +
            abs(locationdata['loc'][i][1] -cashier[1])
        d_list.append(d)
    d_list = d_list/max(d_list) * 0.06
    return d_list
#p2_list = p2(locationdata)



def p3(locationdata):
    entrance = (48, 34)
    d_list = []
    for i in range(len(locationdata)):
        d = abs(locationdata['loc'][i][0] -entrance[0]) +
```

```
            abs(locationdata['loc'][i][1] -entrance[1])
        d_list.append(d)
    d_list = np.exp(-0.15 * np.array(d_list))
    return d_list
#p3_list = p3(locationdata)



def cost(locationdata):
    p1_list,density = p1(locationdata)
    p2_list = p2(locationdata)
    p3_list = p3(locationdata)
    return sum(locationdata['Price'] * \
        locationdata['Quantity Available'] * \
        (p1_list + p2_list + p3_list))

def plot(locationdata):
    p1_list,density = p1(locationdata)
    f,ax = plt.subplots(1,2,figsize=(20,8))
    p1_list,density = p1(locationdata)
    for i in range(len(locationdata)):
        floorplan[locationdata['loc'][i][0]][locationdata['loc'][i][1]] = 10
    sns.heatmap(floorplan,ax = ax[0])
    sns.heatmap(density,ax = ax[1])
#plot(density,locationdata)

## read_layout_data
floorplan = pd.read_excel('matrix_floorplan2.xlsx')
floorplan = np.array(floorplan)

# department
mincost = 1e8
for k in range(300):
```

```
ID_list = []
Pi_list = []
loc = []
dep_list = []
Q_list = []
Pricelist = []
cost_list = []

for depID,dep in Department_Dict.items(): # loop for each department
    x_list,y_list = np.where(floorplan==int(depID)) # find all the possible
        loacations
    Departmentdata = rankingdata[rankingdata['Department'] == dep]
    number_of_products = 5
    if dep == 'Cell Phones' or dep == 'Audio':
        number_of_products = 2
    Departmentdata = Departmentdata.head(number_of_products)
    top_loc = []
    top_loc_index = []
    while True:
        random_num = np.random.choice(range(len(x_list)))
        if random_num not in top_loc_index:
            top_loc.append((x_list[random_num],y_list[random_num]))
            top_loc_index.append(random_num)
        if len(top_loc) == number_of_products:
            break
    # record the locations
    ID_list += list(Departmentdata['ID'])
    dep_list += [dep]*len(Departmentdata)
    Pi_list += list(Departmentdata['Popularity Index'])
    Q_list += list(Departmentdata['Quantity Available During Flash Sale'])
    Pricelist += list(Departmentdata['Price During Flash Sale (USD) '])
    loc += top_loc
```

```
    locationdata = pd.DataFrame()
    locationdata['ID'] = ID_list
    locationdata['Popularity Index'] = Pi_list
    locationdata['Quantity Available'] = Q_list
    locationdata['Price'] = Pricelist
    locationdata['loc'] = loc
    locationdata['Department'] = dep_list
    costtemp = cost(locationdata)
    print(costtemp)
    if costtemp < mincost:
        mincost = costtemp
        bestdata = locationdata
locationdata = bestdata
```

ID	Department	Major Product Category	Product Type	Make (Brand)	Product (Item)	Popularity Index
0	Computers&Tablets	Printers	All-In-One	Brand P	Wireless All-in-One Printer	**79.15274565**
1	Computers&Tablets	Monitors	LED	Brand P	27" IPS LED FHD FreeSync Monitor, 27f	**76.03187124**
2	TV&Home Theater	Video	Blu-Ray Players	Brand BB	Streaming 4K Ultra HD Audio Wi-Fi Built-In Blu-Ray Player	**73.09397356**
3	Computers&Tablets	Laptops	Chromebook	Brand BB	11.6" Chromebook, Intel Atom x5, 2GB Ram, 16GB eMMC Flash Memory	**72.17253619**
4	TV&Home Theater	Video	Blu-Ray Players	Brand DD	Streaming 4K Ultra HD Hi-Res Audio Wi-Fi Built-In Blu-Ray Player	**72.833023**
5	Computers&Tablets	Printers	All-In-One	Brand P	Wireless All-in-One Instant Ink Ready Printer	**71.01732831**
6	TV&Home Theater	Video	Blu-Ray Players	Brand W	4K Ultra HD Blu-Ray Player	**71.55626194**
7	Video Gaming	PC Gaming	Gaming Laptop	Brand P	15.6" Gaming Laptop, AMD Ryzen 5, 8GB Ram, NVIDIA GeForce GTX 1050, 25	**70.0844753**
8	Computers&Tablets	Monitors	LED	Brand P	31.5" IPS LED FHD Monitor	**67.55551202**
9	Appliances	Major Kitchen Appliances	Range/Stove/Oven	Brand M	5.3cu ft Slide-In Electric Range, Stainless Steel	**66.61469616**
10	Appliances	Laundry Appliances	Washer	Brand X	3.8cu ft 12-Cycle Top-Loading Washer, White	**65.79523897**
11	Appliances	Vacuum Cleaners & Floor Care	Robot Vacuum	Brand J	App-Controlled Self-Charging Robot Vacuum	**64.80339985**
12	Appliances	Major Kitchen Appliances	Refrigerator	Brand FF	24.7cu ft French Door Refrigerator, Black Stainless Steel	**65.38564346**
13	TV&Home Theater	TVS 30" to 45"	720p LED HDTV	Brand W	32" 720p LED HDTV	**65.15506488**
14	Computers&Tablets	Monitors	LED	Brand P	32" LED QHD Monitor	**64.35763826**
15	Computers&Tablets	Laptops	Chromebook	Brand BB	11.6" Chromebook, Intel Atom x5, 4GB Memory, 32GB eMMC Flash Memo	**63.65068335**
16	Computers&Tablets	Printers	All-In-One	Brand E	Wireless Color All-in-One Printer	**62.68694554**
17	Computers&Tablets	Laptops	2-in-1 Chromebook	Brand P	2-in-1 14" Touch-Screen Chromebook, Intel Core i3, 8GB RAM, 64GB eMMC Fla	**64.1181038**
18	TV&Home Theater	TVS 30" to 45"	720p LED Smart	Brand O	32" LED 720p Smart TV, H5500 Series	**63.01895024**
19	Computers&Tablets	Laptops	PC Laptop	Brand G	15.6" Touch-Screen Laptop, Intel Core i5, 8GB Ram, 256GB SSD	**62.51767532**
20	Computers&Tablets	Monitors	LED	Brand P	20.7" LED FHD Monitor	**62.51077588**
21	Appliances	Vacuum Cleaners & Floor Care	Upright Vacuum	Brand I	Ball Animal 2 Bagless Upright Vacuum	**62.09499332**
22	Appliances	Major Kitchen Appliances	Dishwasher	Brand FF	24" Tall Tub Built-In Dishwasher, Monochromatic Stainless Steel	**60.70968253**
23	Computers&Tablets	Laptops	2-in-1 Chromebook	Brand V	2-in-1 11.6" Touch-Screen Chromebook, 4GB RAM, 32GB eMMC Flash Mem	**61.13772764**
24	Cameras	Mirrorless Cameras	Camera Package	Brand DD	Full-Frame Mirrorless Camera with 28-70mm Lens, Black	**61.3833958**
25	Computers&Tablets	Monitors	LED	Brand G	27" LED QHD G-Sync Monitor, Black	**60.05613686**
26	Appliances	Vacuum Cleaners & Floor Care	Robot Vacuum	Brand S	App-Controlled Self-Charging Robot Vacuum	**59.5404993**
27	Computers&Tablets	Laptops	2-in-1 Laptop	Brand P	2-in-1 14" Touch-Screen Laptop, Intel Core i5, 8GB RAM, 256GB S	**60.30668362**
28	Computers&Tablets	Desktops and All-In-Ones	Desktop	Brand P	Desktop, Intel Core i7, 8GB RAM, 256GB SSD	**59.84514516**
29	Computers&Tablets	Laptops	2-in-1 Laptop	Brand G	2-in-1 11.6" 4GB RAM 32GB Flash Memory	**59.59292364**
30	Video Gaming	Console Game Systems	Consoles	Brand Y	1TB Star Wars Jedi: Fallen Order Deluxe Edition Console Bundle	**58.63345486**
31	Computers&Tablets	Printers	All-In-One	Brand K	Wireless All-in-One Printer	**58.55725168**
32	Cameras	DSLR Cameras	Body Only	Brand AA	DSLR Camera, Body Only, Black	**59.17259625**

33	Appliances	Vacuum Cleaners & Floor Care	Upright Vacuum	Brand I	Ball Animal + Allergy Bagless Upright Vacuum	**58.23836097**
34	Computers&Tablets	Printers	All-In-One	Brand E	Wireless All-in-One Printer	**56.40405316**
35	Appliances	Major Kitchen Appliances	Refrigerator	Brand M	25.1cu ft Side-by-Side Refrigerator, Fingerprint Resistant, Stainless Steel	**58.44630103**
36	Appliances	Major Kitchen Appliances	Range/Stove/Oven	Brand W	6.3cu ft Slide-In Electric Range with ProBake Convection, Stainless Steel	**58.59616405**
37	Computers&Tablets	Tablets	Tablet	Brand N	12.3" Tablet, 64GB	**56.34967557**
38	Appliances	Major Kitchen Appliances	Range/Stove/Oven	Brand FF	30" Built-In Single Electric Wall Oven, Stainless Steel	**58.01910098**
39	Appliances	Laundry Appliances	Washer	Brand M	4.2cu ft 11-Cycle Top-Loading Washer, White on White	**57.57623309**
40	Computers&Tablets	Laptops	PC Laptop	Brand G	15.6" Touch-Screen Laptop, Intel Core i3, 8GB Ram, 128GB SSD	**57.01850572**
41	Audio	Headphones	Wireless Earphones	Brand D	Wireless Earbud Headphones	**54.81706251**
42	Computers&Tablets	Laptops	PC Laptop	Brand V	11.4" Laptop, AMD A6 Series, 4GB Ram, AMD Radeon R4, 65GB e	**55.9950141**
43	Video Gaming	PC Gaming	Gaming Desktop	Brand F	Gamer Supreme Liquid Cool Gaming Desktop, AMD Ryzen 7 3700X	**57.71163767**
44	Appliances	Laundry Appliances	Dryer	Brand M	7.2cu ft 3-Cycle Electric Dryer, White	**56.5907178**
45	TV&Home Theater	TVS 65"	4K LED	Brand O	65" 4K UHD HDR Smart LED TV, H6500F Series	**54.86422409**
46	Appliances	Major Kitchen Appliances	Range/Stove/Oven	Brand W	30" Combination Double Electric Convection Wall Oven with Built-In Microwave	**55.48215121**
47	TV&Home Theater	TVS 30" to 45"	1080p LED Smart	Brand BB	40" 1080p Smart LED HDTV, 5 Series	**55.78930727**
48	Computers&Tablets	Laptops	2-in-1 Chromebook	Brand BB	2-in-1 12.2" Touch-Screen Chromebook, Intel Celeron, 4GB RAM, 32G	**55.08535192**
49	Video Gaming	Console Game Systems	Consoles	Brand Y	1TB NBA 2K20 Bundle - Black	**53.63345486**
50	TV&Home Theater	Video	Blu-Ray Players	Brand DD	Streaming 4K Ultra HD Hi-Res Audio Wi-Fi Built-In Blu-Ray Player	**54.55801151**
51	Computers&Tablets	Laptops	PC Laptop	Brand P	17.3" Laptop, Intel Core i5, 8GB Memory, 256GB SSD, Jet Black, Maglia Pattern	**54.55751158**
52	Computers&Tablets	Laptops	2-in-1 Laptop	Brand BB	2-in-1 13.3" 8GB RAM 256GB Flash Memory	**54.7323698**
53	Appliances	Major Kitchen Appliances	Range/Stove/Oven	Brand M	5.0cu ft Freestanding Gas Range, Stainless Steel	**54.05789345**
54	TV&Home Theater	TVS 50" - 55"	4K LED	Brand DD	55" 4K UHD HDR Smart LED TV, X800G Series	**53.81098318**
55	Computers&Tablets	Laptops	PC Laptop	Brand P	14" Laptop, AMD A9 Series, 4GB Ram, AMD Radeon R5, 128GB SSD, WIndows	**53.01954997**
56	Computers&Tablets	Laptops	2-in-1 Laptop	Brand P	2-in-1 15.6" 4K Ultra HD Touch-Screen Laptop, Intel Core i7, 16GB	**52.68256235**
57	Appliances	Laundry Appliances	Dryer	Brand FF	7.0cu ft 13-Cycle Electric Dryer, White	**53.38212641**
58	Video Gaming	PC Gaming	Gaming Laptop	Brand C	17.3" Gaming Laptop, Intel Core i7, 16GB RAM, NVIDIA GeForce GTX 1660 T	**51.6227468**
59	Cameras	Mirrorless Cameras	Camera Package	Brand DD	Mirrorless Camera Two Lens Kit with 16-50mm and 55-210mm Le	**52.56707855**
60	Video Gaming	PC Gaming	Gaming Desktop	Brand F	Gamer Master Gaming Desktop, AMD Ryzen 5 3600, 8GB Memory	**52.8586642**
61	Appliances	Major Kitchen Appliances	Refrigerator	Brand W	27.8cu ft 4 Door French Door Refrigerator, PrintProof, InstaView Door-in-Door, Stainless	**52.38240721**
62	TV&Home Theater	Video	Blu-Ray Players	Brand W	Streaming Audio Wi-Fi Built-In Blu-Ray Player	**50.61817257**
63	Computers&Tablets	Monitors	LED	Brand C	24" LED FHD Monitor, Black	**51.43532652**

64	Computers&Tablets	Laptops	2-in-1 Laptop	Brand P	2-in-1 11.6" Touch-Screen Laptop, Intel Pentium, 4GB RAM, 128GB	**51.55828644**
65	Computers&Tablets	Printers	All-In-One	Brand P	Color Wireless All-in-One Printer	**50.81622975**
66	TV&Home Theater	TVS 50" - 55"	4K LED	Brand W	55" 4K UHD HDR Smart LED TV, UK6090PUA Series	**50.59753531**
67	Appliances	Laundry Appliances	Dryer	Brand W	7.4cu ft 10-Cycle Smart Wi-Fi Enabled Electric Dryer, White	**49.89196609**
68	Video Gaming	PC Gaming	Gaming Laptop	Brand C	15.6" Gaming Laptop, Intel Core i5, 8GB RAM, NVIDIA GeForce GTX 1650, 51	**48.6236575**
69	Appliances	Major Kitchen Appliances	Refrigerator	Brand FF	26.8cu ft French Door Refrigerator, Stainless Steel	**49.56519453**
70	Computers&Tablets	Desktops and All-In-Ones	Desktop	Brand P	Intel Core i7 9700, 16GB RAM, NVIDIA GeForce GTX 1660 Ti,	**49.29663458**
71	Appliances	Major Kitchen Appliances	Range/Stove/Oven	Brand FF	5.1cu ft Freestanding Gas Range, Stainless Steel	**49.19563937**
72	Appliances	Vacuum Cleaners & Floor Care	Robot Vacuum	Brand S	App-Controlled Robot Vacuum	**48.01954997**
73	Appliances	Laundry Appliances	Washer	Brand FF	4.3cu ft 12-Cycle Top-Loading Washer, White	**48.7667418**
74	Computers&Tablets	Tablets	Tablet	Brand H	10.1" Tablet, 32GB	**46.71325771**
75	Appliances	Major Kitchen Appliances	Microwave	Brand B	1.6cu ft Over-the-Range Microwave, Black on Stainless	**48.24373146**
76	TV&Home Theater	TVS 70" - 75"	4K LED	Brand DD	75" 4K UHD HDR LED Smart TV, X800G Series	**48.92192919**
77	Computers&Tablets	Desktops and All-In-Ones	All-In-One	Brand P	27" Touch-Screen All-in-One, Intel Core i7, 12GB RAM, 256GB SSD	**47.41776627**
78	Appliances	Vacuum Cleaners & Floor Care	Stick Vacuum	Brand CC	Bagless Cordless Pet Handheld/Stick Vacuum	**45.28148037**
79	Appliances	Vacuum Cleaners & Floor Care	Robot Vacuum	Brand CC	App-Controlled Robot Vacuum	**44.94229361**
80	Computers&Tablets	Desktops and All-In-Ones	All-In-One	Brand P	23.8" Touch-Screen All-in-One, Intel Core i5, 12GB RAM, 256GB SSD	**44.7811959**
81	Appliances	Laundry Appliances	Dryer	Brand W	7.3cu ft 8-Cycle Electric Dryer, White	**45.59821572**
82	TV&Home Theater	Video	Blu-Ray Players	Brand W	Streaming Audio Blu-Ray Player	**43.73736608**
83	Appliances	Major Kitchen Appliances	Refrigerator	Brand W	26.2cu ft French Door Smart Wi-Fi Enabled Refrigerator, PrintProof, Black Stainless	**44.66927125**
84	Computers&Tablets	Laptops	PC Laptop	Brand BB	15" 16GB RAM 256GB Solid State Drive	**44.15886411**
85	TV&Home Theater	TVS 65"	4K LED	Brand DD	65" 4K UHD HDR Smart LED TV, X800G Series	**44.09769499**
86	Video Gaming	Console Game Systems	Consoles	Brand DD	1TB Fortnite Neo Versa Console Bundle - Jet Black	**43.61573172**
87	Computers&Tablets	Laptops	PC Laptop	Brand Y	13.5" 8GB RAM 256GB Solid State Drive	**43.39677324**
88	TV&Home Theater	TVS 65"	4K OLED	Brand DD	65" 4K UHD HDR Smart OLED TV, A8G Series	**43.63640626**
89	Computers&Tablets	Laptops	2-in-1 Chromebook	Brand A	2-in-1 11.6" Touch-Screen Chromebook, Intel Celeron, 4GB RAM, 32GB	**42.62525753**
90	Video Gaming	PC Gaming	Gaming Desktop	Brand Q	Gaming Desktop, Intel Core i5-9400F, 8GB RAM, NVIDIA GeForce G	**42.27395724**
91	Cameras	DSLR Cameras	Camera Package	Brand E	DSLR Camera with 18-55mm IS STM Lens, Black	**42.20140878**
92	Appliances	Major Kitchen Appliances	Dishwasher	Brand L	24" Front Control Tall Tub Built-In Dishwasher, Stainless Steel	**41.81429852**
93	TV&Home Theater	TVS 30" to 45"	4K LED	Brand BB	43" 4K UHD HDR Smart LED TV, 6 Series	**42.17026083**
94	Appliances	Laundry Appliances	Washer	Brand R	4.1cu ft 11-Cycle HE Top-Loading Washer, White	**41.48284805**

95	TV&Home Theater	TVS 70" - 75"	4K LED	Brand BB	75" 4K UHD HDR Smart LED TV, NU6900 Series	**41.56017771**
96	Audio	Headphones	Wireless Earphones	Brand T	Sport Wireless Earbud Headphones	**37.86514033**
97	Computers&Tablets	Laptops	2-in-1 Chromebook	Brand G	2-in-1 14" Touch-Screen Chromebook, Intel Core i3, 4GB RAM, 128GB	**40.95317506**
98	TV&Home Theater	TVS 85"	4K LED	Brand DD	85" 4K UHD HDR Smart LED TV, X900F Series	**41.63757402**
99	Computers&Tablets	Laptops	PC Laptop	Brand P	2-in-1 15.6" Touch-Screen Laptop, Intel Core i7, 12GB RAM, 512GB S	**40.46198504**
100	TV&Home Theater	TVS 50" - 55"	4K OLED	Brand DD	55" 4K UHD HDR Smart OLED TV, A8G Series	**40.63701747**
101	Appliances	Major Kitchen Appliances	Microwave	Brand M	1.6cu ft Over-the-Range Microwave, Stainless Steel	**38.25865362**
102	Video Gaming	PC Gaming	Gaming Laptop	Brand Z	15.6" Gaming Laptop, Intel Core i7, 32GB RAM, NVIDIA GeForce RTX 2060, 5	**39.55912236**
103	Computers&Tablets	Desktops and All-In-Ones	All-In-One	Brand V	23.8" Touch-Screen All-in-One, AMD Ryzen 3-Series, 8GB Memory, 256GB	**39.41227376**
104	Computers&Tablets	Monitors	LED	Brand BB	28" LED 4K UHD Monitor, UE590 Series	**39.02104966**
105	Video Gaming	PC Gaming	Gaming Desktop	Brand F	Gamer Master Gaming Desktop, AMD Ryzen 3 2300X, 8GB Memory	**39.09817268**
106	TV&Home Theater	TVS 65"	4K LED	Brand DD	65" 4K UHD HDR Smart LED TV, X900F Series	**39.48342521**
107	Cell Phones	Cell Phones and Accessories	Headsets	Brand II	Wireless Noise Cancelling Earbud Headphones - Graphite	**36.48225403**
108	TV&Home Theater	TVS 65"	4K LED	Brand BB	65" 4K UHD HDR Smart LED TV, 7 Series	**36.9562276**
109	TV&Home Theater	TVS 65"	4K QLED	Brand BB	65" 4K UHD HDR Smart QLED TV, Q70 Series	**36.95613578**
110	Cell Phones	Cell Phones and Accessories	Headsets	Brand HH	Wireless Wearable Speaker - Black	**36.09897253**
111	TV&Home Theater	TVS 50" - 55"	4K LED	Brand BB	50" 4K UHD HDR Smart LED TV, NU6900 Series	**36.19706054**
112	TV&Home Theater	TVS 50" - 55"	4K LED	Brand BB	50" 4K UHD HDR Smart LED TV, 7 Series	**35.34950366**
113	Cameras	DSLR Cameras	Camera Package	Brand AA	DSLR Two Lens Kit with 18-55mm and 70-300mm Lenses, Black	**34.17552067**
114	TV&Home Theater	TVS 50" - 55"	4K LED	Brand BB	55" 4K UHD HDR Smart LED TV, NU6900 Series	**34.40305937**
115	TV&Home Theater	TVS 50" - 55"	4K LED	Brand EE	55" 4K UHD HDR Smart LED Roku TV, 4 Series	**33.81111243**
116	Appliances	Laundry Appliances	Washer	Brand FF	3.8cu ft 12-Cycle Top-Loading Washer, White	**34.02292926**
117	TV&Home Theater	TVS 30" to 45"	720p LED Smart	Brand EE	32" 720p Smart LED HDTV Roku TV, 3 Series	**33.02369708**
118	TV&Home Theater	TVS 50" - 55"	4K LED	Brand EE	50" 4K UHD HDR Smart LED Roku TV	**32.20428376**
119	TV&Home Theater	TVS 70" - 75"	4K QLED	Brand BB	75" 4K UHD HDR Smart QLED TV, Q70 Series	**32.28169134**
120	TV&Home Theater	TVS 65"	4K LED	Brand BB	65" 4K UHD HDR Smart LED TV, NU6900 Series	**31.93633113**
121	Video Gaming	PC Gaming	Gaming Desktop	Brand Q	Gaming Desktop, Intel Core i7-9700K, 16GB RAM, NVIDIA GeForce	**31.68765236**
122	TV&Home Theater	TVS 65"	4K LED	Brand EE	65" 4K UHD HDR Smart LED Roku TV, 4 Series	**31.02277152**
123	Cameras	DSLR Cameras	Body Only	Brand E	DSLR Camera, Body Only, Black	**29.97627871**
124	TV&Home Theater	TVS 70" - 75"	4K QLED	Brand BB	75" 4K UHD HDR Smart QLED TV, Q60 Series	**29.56167938**
125	TV&Home Theater	TVS 65"	4K QLED	Brand BB	65" 4K UHD HDR Smart QLED TV, Q60 Series	**29.28172852**
126	Video Gaming	Console Game Systems	Consoles	Brand GG	32GB Console - Gray Joy-Con + 2 more items	**28.0321042**
127	Cameras	DSLR Cameras	Camera Package	Brand AA	DSLR Two Lens Kit with AF-P DX NIKKOR 18-55mmf/3.5-5.6G VR &	**27.63815613**
128	Cameras	Mirrorless Cameras	Camera Package	Brand DD	Mirrorless Camera with FE 28-70mm F3.5-5.6 OSS Lens	**27.35861442**

129	Camera	DSLR Cameras	Camera Package	Brand E	DSLR Two Lens Kit with EF-S 18-55mm IS II and EF 75-300m	**26.63835887**
130		Cell Phones and Accessories	Headsets	Brand W	Wireless Bluetooth Headset - Black	**24.86800337**
131	TV&Home Theater	TVS 65"	4K QLED	Brand BB	65" 4K UHD HDR Smart QLED TV, Q80 Series	**26.10049999**
132	Cameras	Mirrorless Cameras	Camera Package	Brand E	Mirrorless Camera with Lens	**21.92485888**
133	TV&Home Theater	TVS 70" - 75"	4K LED	Brand BB	70" 4K UHD HDR Smart LED TV, 6 Series	**19.36932806**