BUSINESS MODEL OF BIGBASKET.

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Introduction

Technology has fundamentally modified patron behavior and converted the way industries painti
ngs. The related commerce generation has arrived in lots of industries, especially rapid shifting con
sumer items (FMCG). these days, customers are comfy with the advantages of virtual buying and a
nticipate similar enjoy ingrocery enterprise. The physical and digital worlds are getting more diffi
cult to outline. humans are no longer shopping completely on-line or offline, as an alternative they
maybe taking a mixed approach using anything channel suits their desires exceptional.
The maximum successful shops and manufacturers will be at the intersection of the physical and di
gital worlds. Taking gain of generation may want to make shoppers happier and provide them
freedom on every occasion and any place they'll shop (Nielsen, 2015).
Eagerness to make use of superior retailing choices is maximum extended in creating markets with
in the Asia-Pacific (60%), Latin America (60%), Africa/middle East districts (fifty nine%), and
trails in Europe (forty five%) and North us (fifty two%) (Nielsen, 2015).
The increasing wide variety of portable and broadband penetration in particular in growing international locations, has additionally helped on-line grocery deals. Asia-
Pacific reliably surpasses the global average for on line shopping. In e-trade, product choice matters. Virtual basket does no longer truly reflect a physical basket. Indeed, the
correlation among each virtual and bodily basket is often a opposite one. as an example, in
US, the combination of online product sales is 60% for non-meals products and forty% for food products. Alternatively, the product sales in bodily stores are 40% and 60% respectively
for non-meals and food merchandise. it is the precise reverse among in-store and online shop (Nielsen, 2015).
Nielsen’s studies concerning “The destiny of Grocery” cautioned there are four elements that have an impact on e-trade fulfillment based totally on consumer product selection (Nielsen, 2015): inventory-up, rate, urgency, and
inspection. Each stock-up and price act as the enablers that result in patron buy whilst both urgency and inspection act because the limitations that
would prevent customer to buy product from an e-commerce. In some cases, there
are huge opportunities in area of interest markets including healthful ingredients and uncommon p
roducts. The Nielsen research showed that nowadays’s consumers are greater aware about the
freshness and naturalness of products which can be useful to
research and identify the user conduct of an e-trade, facts mining is the appropriate technique to
dig deeper and find client insights. The virtual trace left by means of the customer each time they
use the e-commerce can be recorded and analyzed.
The statistics mining is useful to discover enterprise insights and locate the exceptional business approach. Essential connections and causalities are the way to supervise massive data and permitting agencies to peer more specific snapshot shots of their costumer behavior. Facts mining also discovers the essential styles unexpectedly, exactly, and with relevance. It gives a miles-wanted aggressive advantage in high-threat surroundings via supplying insights into purchaser-shopping for patterns to manual the product presenting, deliver chain planning, and execution (Savitz, 2012). The consumer insights derived from big records can permit marketers to layout contextual advertising and centered advertising in order that each consumer can get the excellent supplying and advertising message primarily based on their dynamic historic behavior. Contextual advertising is a large aspect. In virtual industries, many clients disregard advertisements consisting of banner, video, backed search if it isn't related to their needs or possibilities. As entrepreneurs, we ought so one can adapt and cognizance to create classified ads and campaigns primarily based on context. Digital experience and relevant commercials are the purchaser’s expectation. These days, contextual advertising is common because the costumers’ online behaviors are by and large being tracked. Profile tracker on website browsers and cell gadgets are capable of know what we search, which internet site we visit, or wherein we're positioned. By means of the use of these facts, entrepreneurs are capable of target greater accurately to interact clients. Contextual marketing is a manner to boom patron’s revel in by using using customized marketing in actual-time behavior (Delane, 2016). Moreover, the virtual life can be traced by understanding the weather, channel desire, region, enterprise or non-public, buy records, beyond conduct, device, time of day, and language used. This study focuses on the implementation of contextual advertising in grocery e-trade in India. India’s grocery market has swiftly grown although it is still has a small marketplace share. The marketplace percentage estimated is INR 22, 5 trillion (USD 350 billion) and stays as the top 10 of food and grocery market inside the world. The marketplace growth is round 10%-12% CAGR between 2010 and 2015. The dimensions of online grocery market is still underneath 1% of average food and grocery income at around INR 40 billion (USD 0.6 billion). However, the increase itself reached 35% CAGR with market penetration round 2.3 three% (EY, 2015). Notwithstanding of fast increase, the Indian grocery e-trade has spent huge advertising and marketing prices inefficiently, over and on top of the negative margins. They have paid many famous actors to become their brand ambassadors, marketing on diverse media particularly print and out of doors commercials. Some grocery e-trade gamers even supply an offer to
the retailers to keep promoting in their e-commerce, which accelerated their burn costs. Then again, Indian users have grown to be smarter; they may be discount-hungry and emerge as disloyal customers.

A good way to hold availing the 20 percent cut price, human beings orders groceries from four to five exclusive cell numbers they’ve within the same household. Most e-shops offer 20 percent bargain only on first purchase, usually related to a cellular number. The bargain hungry Indian customers went away as soon as the schemes stop. Except, the opposition isn’t always simplest between grocery e-trade however also with the wandering pushcart. Not one of the apps has yet been able to compete with the wandering pushcart owner, promoting fresh veggies in India’s neighborhoods. The wandering veggie vendor offers credit, knows customers by using their names, and frequently prepares orders before touchdown at the doorsteps of his shoppers (Julka, 2016).

With the implementation of contextual advertising, grocery e-commerce can examine the client behavior and select the most effective advertising and marketing method and engaging advertising to get a greater green go back at the advertising funding. The preceding burn charge of cash spent on mass advertising can be allocated at once to online-centered marketing this is predicted to be more attractive to the customers based totally on their behavior. The income promoting approach can vary from bargain, bundling, loose object, or referral depends on their previous shopping for pattern. Moreover, it can also dynamically trade between promotional program and loyalty application depends at the converting sample of purchaser. This manner, it is able to restriction the abuse of bargain hunting from disloyal customers because every consumer could be provided unique promotions while growing client loyalty by providing particular loyalty packages to the chosen capacity customers on customer buying pattern. The detailed objectives are expressed as follows:

The focus of this research is to find the most suitable and effective contextual marketing for BigBasket based on the customer buying pattern. The more detailed formulation of the problem in this study is expressed as follows:

1. How do we identify customer purchase behavior per product category based on their buying pattern?

2. How many customer clusters are formed per product category and what is the customer profile?
3. Which is the best time to deliver notifications and promotional messages to each customer cluster?

The research objectives are to find the most suitable and effective contextual marketing for BigBasket based

1. To identify customer buying pattern based on RFM analysis, in general, and per product category, in particular.

2. To identify how many customer clusters and customer profile are formed in every product category based on RFM analysis and KMeans clustering.

3. To find time-based customer buying pattern that would help to decide the situation to deliver notifications and promotional messages to each customer clu

Literature Review

Grocery E-commerce

Electronic trade (E-trade) is a business platform on telecommunication networks to proportion facts, preserve dating, and conduct transaction related to commercial enterprise (Vladimir, 1996). E-trade has been booming recently, but the exercise it denotes originated nearly 1/2-century in the past inside the Berlin airlift. It started out with the EDI (digital facts interchange) for internal firms, the laptop-to pc exchange of standardized digital transaction documents, the whole transaction for grocery e-trade platform has reached USD 48 billion a 12 months till June 2016 and the e-trade market proportion is four.4% of all FMCG sales (Kantar Worldpanel, 2016). The FMCG market growth is flat however the e-trade channel for FMCG is developing 1.6% in the identical period (KantarWorldpanel, 2016). Massive data Analytics huge records is information that exceeds the processing potential of conventional database systems.

In these days’s commercial enterprise, the idea of massive statistics has been analyzed from many points of view and in lots of research. IBM as one of the leading employer for massive facts analytics determined four aspects of large facts analytics: volume, velociTy, range, and veracity (IBM, 2011). Quantity is one of the aspects associated with the dimensions of statistics. The facts need to be big and have essential understanding. Speed is the time wished for the huge facts to be processed. In large facts, timing is essential and speedy reaction is needed. Records nowadays may be analyzed in actual time and
the quicker information is processed, the extra green it's miles. Range is related to how the huge statistics can incorporate. The records might be in different bureaucracy who includes established and unstructured. The information might be from open assets consisting of social media or internal from the employer. Veracity is the uncertainty of information. It’s miles approximately the satisfactory of the data whether or not we could accept as true with the used records to make selections. massive facts is wanted whilst the statistics is simply too large (extent), moves too speedy (pace), doesn’t suit the shape of your database architectures (variety), or with uncertain exceptional (veracity) as a way to gain fee from this data (IBM, 2011).

**Contextual Advertising and Marketing**

Contextual marketing is an approach and alertness of advertising in a particular state of affairs this is contextualized and custom designed (Carson, Enright, Tregear, Copley, Gilmore, Stokes, Deacon, 2002). There are some factors which are able to simplify the contextual marketing via the use of inter-structured, inter-related and synergistically affects that become an interface among the company and the market firms (marvel, 2012).

Contextual marketing could be performed in online and cellular advertising and marketing that offers a customized commercial based on person facts or past user behavior along with current website surfing. The goal contextual marketing is to offer the user commercial that represents services and products that they may be already interested in (surprise, 2012).

**Targeted Advertising**

Targeted advertising is a type of advertising used by online advertisers that utilized refined techniques to the most receptive audiences with specific characteristics, depending on the product or person the advertiser is promoting (Plummer & Rappaport, 2007). Moreover, these characteristics could be in many forms: (1) demographic (race, economic status, sex, age, the level of education, income level, and employment), (2) psychographic (consumer’s values, personality, attitudes, opinions, lifestyles, and interests), (3) behavioral variables (browser history, purchase history, and other recent activities). Targeted advertising would be more cost effective since it only focused on certain characteristics and targeted only costumers with high preference to receive the advertisement.

**Buying Pattern**
Costumer buying behavior is a buying behavior of end costumer for personal consumption and could be individuals or households (Kumar, 2010). Buying pattern shows how costumers purchase goods or services (Kahn, 2012). How the costumers purchase could be shown by frequency, quantity, duration, etc. Buying patterns could also be related to demographic, geographical, and psychological of costumers. Further understanding of buying patterns will give firms benefits for decision making in the field of strategic marketing, segmentation, distribution, and promotion (Kahn, 2012).

**RFM (Recency, Frequency, and Monetary)**

RFM is the abbreviation of Recency, Frequency and Monetary. RFM method is one of a marketing technique that is used to analyze costumer behavior based on recency, frequency, and monetary (Birant, 2011). Recency refers to how recently a customer has made a purchase and is usually measured by days or time units. Frequency refers to how often the customer purchases. Monetary refers to how much the customer spends and it is shown in currency unit. RFM method is able to show the customers segmentation by dividing the customers into many groups based on the RFM number which will shows the similarity of customer behavior and buying pattern.

**K-Means Clustering**

The K-means method is a clustering method that choose K center to minimize the average squared distance between each point and its closest center. K-means clustering method is one of the oldest and most important methods in computational geometry. A survey of data mining techniques showed that clustering is the most popular technique that is used in scientific and industrial applications (Berkhin, 2002). Determining the most appropriate number of clusters is assisted by elbow method. The method is a validation and interpretation of the clustering consistency.

**Company Profile**

The Bigbasket story begins in 1999. The founders are VS Sudhakar, Hari Menon, Vipul Parekh, Abhinay Choudhari, and VS Ramesh. They started their first online shopping business in India called Fabmart.com. They started an online groceries business in 2001 as part of Fabmart. They also succeeded to build an offline store named Fabmall that was a chain of grocery supermarkets in the South of India. In 2006, they sold their business. In 2011, the team got back and launched Bigbasket.com. Bigbasket.com are available in in Bangalore, Hyderabad, Mumbai, Pune, Chennai, Delhi, Noida, Mysore, Coimbatore, Vijayawada-Guntur, Kolkata, Ahmedabad-Gandhinagar, Lucknow, Kanpur, Gurgaon, Vadodara, Visakhapatnam, Surat, Nagpur, Patna, Indore and Chandigarh Tricity. Payment can be processed online using debit or credit card and
also by COD (Cash On Delivery). Bigbasket.com divides their products based on several categories as follows: (1) fruits & vegetable, (2) grocery & staples, (3) bread, dairy & eggs, (4) beverages, (5) branded foods, (6) personal care, (7) household, (8) imported & gourmet, (9) meat. There are also sub-category and sub-sub-category in each category. Bigbasket.com set aside some spot in their website page for the advertisement from BigBasket.com itself. It starts from the homepage of BigBasket.com. There are two types of web banner advertising. First, the slideshow web banner. It consists of promotion such as discount and new products. If the banner is clicked, it will direct customers to the product web page. Secondly, the static web banner. It consists of discount (deals of the week) and products. If the home page is scrolled down, there are still many more banners. The advertising spot in homepage is different with the advertising spot in each shop category. The only advertising spot is slideshow banner in each product category. There are several advertisements and all the advertisements are related to the category itself. BigBasket.com also provides a dedicated promotional web page. It consists of discounts, promotions, and bundle packs. BigBasket.com performs email marketing to the customers. There are some clickable parts such as product category that links directly to the website page. There may be more e-mails towards customers that BigBasket.com does as a usual ecommerce. SMS promotion is also available in BigBasket.com. Unfortunately there is no sample from BigBasket.com available in intern

Online Application/Website

1. Website:- www.bigbasket.com
Methodology

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Recency</th>
<th>Frequency</th>
<th>Monetary</th>
<th>Customer Profile</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>High</td>
<td>High</td>
<td>High</td>
<td>Most Valuable Customer</td>
</tr>
<tr>
<td>C2</td>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>Barnacle</td>
</tr>
<tr>
<td>C3</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>Big Basket Shopper</td>
</tr>
<tr>
<td>C4</td>
<td>High</td>
<td>Low</td>
<td>Low</td>
<td>First Timer</td>
</tr>
<tr>
<td>C5</td>
<td>Low</td>
<td>High</td>
<td>High</td>
<td>Chum Valuable Customer</td>
</tr>
<tr>
<td>C6</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>Chum Barnacle</td>
</tr>
</tbody>
</table>
### Table 1. Eight Types of Customer Profile

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>C7</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
<td>Chum Big Basket Shopper</td>
</tr>
<tr>
<td>C8</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Stranger</td>
</tr>
</tbody>
</table>

### Table 2. Variable Descriptions of the Raw Dataset.

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Data Type</th>
<th>Description &amp; Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Member</td>
<td>Character</td>
<td>Member ID or the unique registered user ID of buyers in BigBasket.com</td>
</tr>
<tr>
<td>Order</td>
<td>Numeric</td>
<td>Order number or unique Invoice Number ID that is auto generated for every order checkout that occurred.</td>
</tr>
<tr>
<td>SKU</td>
<td>Numeric</td>
<td>Stock Keeping Unit or the product item unique ID</td>
</tr>
<tr>
<td>Created On</td>
<td>Character</td>
<td>Contains the date and time of customer purchase that consists of year, month, date, hour, minute of purchase.</td>
</tr>
<tr>
<td>Description</td>
<td>Character</td>
<td>Short description of the product item bought. Every product description is a subset of a subcategory and every subcategory is a subset of product category</td>
</tr>
</tbody>
</table>

### Research Flow

This research is designed to identify the customer profile of Bigbasket.com, an e-groceries in India, based on RFM (Recency, Frequency, Monetary) analysis per product category so that the marketer could devise the most suitable marketing strategy or promotional offer for each distinct customer. Customer segmentation analysis is conducted using K-Means clustering technique. The research flow started with raw data that provided by Magister Manajemen UI (MM-UI). The next step is data pre-processing in order to be able to perform data processing. The data preprocessing starts with data error elimination, followed by the data categorization based on the product description. Date and time also need to be formatted since there are different formats in the raw data. Next, the information regarding hours, days, and months will be extracted from the data. Then, the new dataset based on category are ready to be processed. The dataset will be based on 9 (nine) categories as follows: (1) all categories, (2) beverages, (3) branded foods, (4) bread, dairy, and eggs, (5) fruits and vegetables, (6) grocery and staples, (7) household, (8) meat, and (9) personal care. The data processing will be using RFM (Recency, Frequency, and Monetary) analysis. Then, the RFM result will be clustered using K-Means clustering to obtain customer segmentation. To distinguish the RFM profile with each other’s, the R, F, or M value is examined whether above or below the average value by assigning high (↑) or low (↓). The high or ↑ sign means that the Recency is below the mean value, while the low or ↓ sign means that the Recency is above the mean value. For the recency, the smaller number would be assigned high
because of the customer just bought recently. In the other hand, the high or ↑ sign means that the Frequency or Monetary element is above the mean value, while the low or ↓ sign means that the Frequency or Monetary element is below the mean value. The ideal customers have high recency since they just bought the product recently, have high frequency of shopping, and have high monetary value with big amount of spending. So, there will be 8 possible combinations (2x2x2) of customer profiles based on the RFM analysis. It will also be analyzed based on purchase time. From all the analysis, the contextual marketing design could be formed.

- **The Raw Data**

The raw data used in this study is provided by MM-Ul that is obtained from public sales transaction sample data from Big Basket, a leading grocery e-commerce in India. The raw dataset is derived from the Big Basket sales transaction records occurred during 2011-2014 period. It consists of five variables (column) and 62,136 rows.

- **Data Analysis & Result**

The RFM Analysis is performed to all the 9 (nine) dataset. First, we calculated the Recency, Frequency, and Monetary value. The RFM Data is clustered according to their value of Recency, Frequency, and Monetary. The RFM (Recency, Frequency, and Monetary) method needs to be modified to RFQ (Recency, Frequency, Quantity). The quantity assumption is that every row in transaction represents one item bought. If the monetary information is known, it might be more accurate to generate the RFM number. However, the quantity itself is able to represent the monetary value. The number of cluster is determined following the “elbow” point rule from 19 iterations of K-Means analysis from k=2 to k=20 and each iteration uses the mean value of 100 random within of sum of squares value. After running the K-Means Script, it generated the K-value curve. The number of k (clusters) chosen for Kmeans analysis is determined from the elbow position on the curve. The iteration of K-means helps us decide the k value for clustering. Afterwards, the graphic of k-value and Average Total within Sum of Squares is examined and the result is shown in the figure below, all category products as example
Figure 3. The Curve of k-value and Average Total within SS (all category)

Figure 4. Clusplot All Categories Data

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Recency</th>
<th>Frequency</th>
<th>Monetary</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>13.16528</td>
<td>130.55556</td>
<td>1105.3333</td>
</tr>
<tr>
<td>2</td>
<td>22.68012</td>
<td>89.81818</td>
<td>696.5000</td>
</tr>
<tr>
<td>3</td>
<td>18.87093</td>
<td>77.34211</td>
<td>543.8947</td>
</tr>
<tr>
<td>4</td>
<td>36.43366</td>
<td>36.11111</td>
<td>437.5000</td>
</tr>
<tr>
<td>5</td>
<td>469.14583</td>
<td>24.00000</td>
<td>447.0000</td>
</tr>
</tbody>
</table>
Table 3. K-Mean Clustering Result of All Categories Data

From the curve in Figure 3, the appropriate elbow point should be k=5. Then, k-means algorithm with k=5 is selected. The R Script executes k-means algorithm with k=5 and is described as follows. The output is shown in the figure below. The clustering process in Figure 4 is done by K-Means itself. The membership is singular. Each cluster will have different members from the other clusters, no overlaps. The next step is to examine the result of K-means clustering and evaluate each cluster. Now that each cluster has its RFM value, it should be compared to the mean RFM for all categories data and the output is as shown in table 4. From the table above, the most recent transaction is in the same day as the last day of transaction from the raw data given. The least recent transaction happened in 469.14 days ago. The mean of recency is 29.37 days ago which means the customer in average usually made a purchase in every 29.37 days, or almost every month. The least frequent customer purchased 24 times within 4 years but the most frequent customer purchased 202 times within 4 years. The average customer purchase frequency is 79.11 times within 4 years. The least number of product item bought in 4 years was 402 items. The highest number of product item bought in 4 years is 1,438 items. The average monetary is 586.2 items bought within 4 years. The RFM value of each cluster is compared to the mean value, in order to determine whether the RFM value of each is cluster is above average or below average. The data analysis will be performed in all 9 (nine) categories and the results are as follows.

- **Beverages Category**

The RFM data showed that the categories are divided into 3 (three) customer classes as follows: most valuable, first timer, and leaving. There are 40 most valuable members (45.45%), 28 first timer members (31.82%), and 20 leaving customers (22.37%). The beverages category is dominated with valuable customers. The mean recency is 195.2 days ago. The mean frequency is 11.41 within four years. The mean monetary is 13.1 within four years per member.

- **Branded Food Category**

The RFM data showed that the category has 4 (four) customer classes as follows: most valuable, churn, first timer, and leaving. There are 35 most valuable members (33.02%), 12 churn members (11.32%), 20 first timer members (18.87%), and 39 leaving customers (36.79%). The branded food category is dominated with most valuable customers. The mean recency is 65.35 days ago. The mean frequency is 31.62 times within four years. The mean monetary is 64.58 items within four years per member.

- **Bread, Dairy, and Eggs Category**
The RFM data showed that the category has 3 (three) customer classes as follows: most valuable, first timer, and leaving. There are 38 most valuable members (37.62%), 34 first timer members (33.66%), and 29 leaving customers (28.71%). The bread, dairy, and eggs category is dominated by most valuable customers. The mean recency is 148.25 days ago. The mean frequency is 18.3 times within four years. The mean monetary is 24.67 items within four years per member.

- **Fruits & Vegetables Category**

The RFM data showed that the category has 3 (three) customer classes as follows: most valuable, first timer, and leaving. There are 39 most valuable members (36.79%), 65 first timer members (61.32%), and 2 leaving customers (1.89%). The fruits and vegetables category is dominated by first timer members. The mean recency is 63.63 days ago. The mean frequency is 43.83 times within four years. The mean monetary is 243 items within four years per member.

- **Grocery & Staples Category**

The RFM data showed that the category has 3 (three) customer classes as follows: most valuable, first timer, and leaving. There are 29 most valuable members (27.36%), 53 first timer members (50%), and 19 leaving customers (22.64%). The Grocery & Staples category is dominated by first timer members. The mean recency is 36.63 days ago. The mean frequency is 72 times within four years. The mean monetary is 220.4 items within four years per member.

- **Household**

The RFM data showed that the category has 2 (two) customer classes as follows: most valuable and leaving. There are 75 most valuable members (72.82%) and 28 leaving customers (27.18%). The household category is dominated by most valuable members. The mean recency is 181.89 days ago. The mean frequency is 9.07 times within four years. The mean monetary is 10.75 items within four years per member.

- **Meat**

The RFM data showed that the category has 2 (two) customer classes as follows: most valuable and leaving. There are 6 most valuable members (75%) and 2 leaving customers (25%). The meat category is dominated by most valuable members. The mean recency is 170.70 days ago. The mean frequency is 4.75 times within four years. The mean monetary is 5.5 items within four years per member.

- **Personal Care**
The RFM data showed that the category has 2 (two) customer classes as follows: most valuable and stranger. There are 64 most valuable members (62%) and 39 stranger customers (38%). The personal care category is dominated by most valuable members. The mean recency is 151.46 days ago. The mean frequency is 10.63 times within four years. The mean monetary is 13.34 items within four years per member.

<table>
<thead>
<tr>
<th>Description</th>
<th>Recency</th>
<th>Frequency</th>
<th>Monetary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>0.000</td>
<td>24.00</td>
<td>402.0</td>
</tr>
<tr>
<td>Mean</td>
<td>29.368</td>
<td>79.11</td>
<td>586.2</td>
</tr>
<tr>
<td>Max</td>
<td>469.146</td>
<td>202.00</td>
<td>1438.0</td>
</tr>
</tbody>
</table>

Table 4. Mean for All Categories

Table 5. Peak Hour in Bigbasket.com Based on Customer Profile

Peak Hour based on Customer Profile

The table below shows the buying patterns of the most valuable customers. The peak hour is at 9 am for each category except for meat. In the evening, the sales rise again but not as concentrated.
as the morning. The time span for the evening peak hour is from 21-22. The recommended time to send any kind of notification and message blast is in the morning before the peak hour. For non-busy hour, it is a good time to do flash sale.

- **Conclusions**

1. The customer buying pattern is identified by using RFM and clustering method. The RFM method is able to show the recency, frequency, and monetary value of customers. After the RFM value of each customer is known, customers are clustered into several groups using K-Means. The clustering method forms different clusters with different RFM values and characteristics. The customers in the same cluster are likely to have similar buying behaviors.

2. The customer clusters can be formed and profiled differently based on every product category. Each customer can be classified as a different profile depending on the product category.

3. The best time to deliver notifications and personal messages is near or at the beginning of the peak hour.

4. The offering content of contextual marketing and targeted advertising can be designed by adapting to the customer profile and the timing of message delivery based on the peak hour of customer buying time.

- **Managerial Implication**

The implication of this research is that the grocery e-commerce can design the most suitable contextual marketing and targeted advertising based on customer profile matrix and the hourly purchase behavior. Therefore, the company can deliver efficient marketing promotions or offers that are relevant to each customer at the best timing based on their changing buying pattern.

- **Contextual Marketing Design**

Set Marketing Objectives Based on the RFM customer profile obtained, customers can be classified as different clusters depending on the product category. By knowing the customer clusters, we could set the marketing plan differently and reduce the unnecessary marketing cost. Giving offers to churn valuable customer and churn big basket shopper are the highest priority. Secondary priority goes to most valuable customer and big basket shopper. Third priority goes to the first timer and barnacle customer. And the last are churn barnacle and stranger customers that need no special treatment. Select Targeted Promotional Offers Map the marketing objectives into a marketing strategy and the template of promotional offers and messages. For the Bigbasket case, it can be defined as follows. Select Advertising Channel The first channel is the banner in every product category. The second one is direct mail marketing. And thirdly is SMS. Timing of
Ads Delivery As shown in Table. 5, the peak hour in general is around 9 am in the morning and 8 pm at night. Some of the categories also have peak hours outside those hours. If Bigbasket would like to send notifications and message blast, it is recommended to send them in the morning and evening before the peak hour.

- **Targeted Advertising**

Now that we already have the contextual marketing design, the next step is to put it into action in targeted advertising logic that can be implemented using information technology. The most important thing is the logic or algorithm of the targeted ads. So, whenever a customer visit Bigbasket.com or Bigbasket app, the system should get the ID of the visitor, which could be based on the IP address (if the user does not log in) or the user ID (if the user logs in). The system then read the member ID. If the system already receives the member ID then the information regarding customer cluster could also be obtained from the customer cluster database.

Targeted Direct Mail Direct mail is sent to each customer differently depending on the customer profile.

Targeted App and SMS Notification SMS should only contain one or two offers based on the highest priority message. The timing to send SMS is at the beginning point of peak purchase. For example, if a member’s peak purchase is between 10 to 12, then the notification should be sent at 10 am.

➢ **References.**


