

Exploring a Hypothetical Store's Shopper Data Dataset in Anticipation of the Black Friday Holiday Season

Data Science: Capstone Project for Harvardx Professional Data Science Certificate
(Choose your own project: PH125.9x)

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1 Chapter 1

1.1 Overview

The purpose of this project is to apply advanced Machine Learning (ML) techniques to a publicly available dataset as part of the “*Data Science: Capstone’ course (PH125.9x)*” offered by edX HarvardX. The project goes beyond basic analysis, focuses on exploring and analyzing the data using ML algorithms. The goal is to gain insights from the analysis and effectively communicate the process and findings.

1.2 Introduction

The term “*Black Friday*” didn’t start as a shopping related term. Instead, it emerged during a financial crisis. This explanation looks back at the historical context that led to the term’s creation, tracing its beginnings to a significant event that happened on a memorable day in September. The term “*Black Friday*” first appeared in history on September 24, 1869 [1].

“*Black Friday*” is a major shopping event that happens on the day after “*Thanks giving*” in the United States. It’s seen as the start of the Christmas shopping season and is known for big discounts and special offers from stores. “*Black Friday*” is one of the busiest shopping days of the year, with shoppers lining up early in the morning to get great deals.

In recent years, online shopping’s popularity has led to the rise of “*Cyber Monday*”, which takes place the Monday after “*Black Friday*” and offers online sales and discounts. “*Black Friday*” is now observed in other parts of the world, like Canada, the United Kingdom, and Australia [2].

In retrospect, the origins of “*Black Friday*” emerge not as a celebration of consumerism, but rather as a historical marker of a financial crisis of considerable magnitude. The term’s inception, intertwined with the machinations of Gould and Fisk, serves as a poignant reminder of the intricacies and fragility inherent in the financial realm. The events of that fateful September day in 1869 stand as a testament to the far-reaching consequences of unscrupulous financial manipulation, casting a somber and profound shadow over the narrative of “*Black Friday*”.

The modern incarnation of “*Black Friday*” has evolved into a grand spectacle characterized by an array of sales, enticing promotions, and serpentine queues forming outside retail establishments. Esteemed retailers including Target, Best Buy, Amazon, among others, eagerly anticipate this annual occasion, anticipating that consumers will seize the opportunity to partake in extraordinary bargains and exclusive offers.

Beyond its immediate scope, the term “*Black Friday*” has also catalyzed the emergence of additional retail-themed observances, including “*Cyber Monday*,” “*Small Business Saturday*,” and “*Giving Tuesday*”[3]. Here in lie several noteworthy statistical highlights extracted from the events of “*Black Friday*” in the year 2018:

1. Foot traffic of patrons within physical stores experienced a marginal decline of 1.7% as compared to the preceding year of 2017.
2. Online consumer expenditures witnessed a robust surge, tallying an impressive \$6.22 billion, reflecting a substantial increase of 23.6% from the corresponding figures of 2017.

1.3 Executive Summary

The main goal of this project is to harness the power of ML models and vector support techniques to analyze and forecast the sales volume of “*Black Friday*.” Intend to explore a variety of factors, including Gender, Top Sellers, Age, City, Marital Status, and occupation, to gain insights into what drives sales during this event.

To achieve this objective, employ data transformation and feature engineering techniques. These processes are crucial for enhancing the accuracy of predictions. Strive to optimize the models by utilizing various

approaches and methods. As part of this project, delve into several modeling techniques to assess their effectiveness in predicting “*Black Friday*” sales. Throughout the project, utilize various evaluation metrics to measure the performance of each modeling approach.

Aim is to identify the most suitable model that provides the most accurate predictions. This project not only involves data analysis and ML but also the critical task of selecting the most effective model to improve understanding of “*Black Friday*” sales patterns.

1.4 Objectives

1. Analyze historical Black Friday sales data:

- i. To explore and understand the patterns and trends in consumer behavior and sales during past “*Black Friday*” events.
- ii. To investigate how different demographic factors, such as age, gender, and occupation, influence purchasing behavior.
- iii. To assess the impact of various product categories on overall sales.

2. Identify key factors influencing consumer purchasing decisions:

- i. To determine the most significant variables that drive consumers’ purchasing decisions during “*Black Friday*”.
- ii. To analyze the relationship between consumer demographics, product types, and purchase amounts.
- iii. To explore how factors such as city category, years of stay in the current city, and marital status affect buying behavior.

3. Predict future sales trends using ML algorithms:

- i. To develop predictive models that can forecast future sales based on historical data.
- ii. To evaluate the performance of different ML techniques in predicting purchase amounts.
- iii. To create reliable and accurate models that retailers can use to anticipate sales trends and prepare accordingly.

4. Provide actionable insights for retailers to enhance their sales strategies:

- i. To offer data-driven recommendations for retailers to optimize their inventory and marketing strategies.
- ii. To identify target customer segments that are most likely to generate higher sales.
- iii. To suggest effective promotional strategies and personalized marketing approaches based on consumer behavior analysis.

These objectives aim to equip retailers with valuable insights and tools to maximize their success during “*Black Friday*” and beyond, ensuring they can meet customer demands efficiently and enhance overall sales performance. The “*Black Friday*” dataset from a retail store is analyzed in this project to understand customer behavior and identify key trends. The dataset includes various features such as customer demographics, product details, and purchase information. The primary goal of this project is to build predictive models to forecast future sales and improve marketing strategies.

1.5 Key steps performed in this project

1. Data cleaning to handle missing values and incorrect data entries.
2. Data exploration and visualization to gain insights into customer behavior and purchase patterns.
3. Implementation of multiple predictive models, including advanced techniques beyond linear and logistic regression.
4. Evaluation of model performance using appropriate metrics.

2 Chapter 2

2.1 Method and Analysis

In Exploratory Data Analysis (EDA), methods and analysis refer to the techniques and approaches used to examine and understand the characteristics of a dataset without making any formal assumptions about the underlying distribution or relationships.

EDA is a crucial step in the data analysis process as it helps uncover patterns, trends, anomalies, and relationships within the data. Here's a brief overview of methods and analysis in EDA:

1. **Descriptive Statistics:** Descriptive statistics provide a summary of the main aspects of the dataset. Measures like the mean (average), median (middle value), and mode (most frequent value) offer insights into the central tendency of the data.
2. **Range and Variability:** Understanding the range (difference between the maximum and minimum values) and variability (standard deviation, interquartile range) helps gauge the spread of the data.
3. **Frequency Distribution:** Creating histograms and frequency tables helps visualize the distribution of values in the dataset.
4. **Data Visualization:**
 - i. **Histograms:** A graphical representation of the distribution of a dataset, showing the frequency of different values.
 - ii. **Box Plots (Box-and-Whisker Plots):** Box plots provide a visual summary of the distribution, including the median, quartiles, and potential outliers.
 - iii. **Scatter Plots:** Used to explore relationships between two continuous variables. Each point on the plot represents a data point.
 - iv. **Pair Plots:** For multivariate analysis, pair plots display scatter plots for all pairs of variables in the dataset.
 - v. **Heatmaps:** Visualizing the correlation matrix to understand relationships between variables.
5. **Data Cleaning:** Identifying and handling missing data. Dealing with outliers that might affect the analysis.
 - i. **Dimensionality Reduction:** Techniques like Principal Component Analysis (PCA) or t-Distributed Stochastic Neighbor Embedding (t-SNE) can be applied to visualize high-dimensional data in a lower-dimensional space.
 - ii. **Pattern Recognition:** Identifying patterns or trends in the data that might indicate interesting features or relationships.
 - iii. **Statistical Tests:** Conducting basic statistical tests to check assumptions or explore relationships, though this is more common in confirmatory data analysis.
6. **Interactive Exploration:** Using tools like interactive dashboards or applications to explore the data dynamically.

The goal of EDA is to gain insights into the data, generate hypotheses, and inform the next steps in the analysis. It's a flexible and iterative process that allows analysts to adapt their approach based on the discoveries made during exploration.

2.1.1 Exploratory Data Analysis (EDA)

Commencing endeavor, initiate by loading the dataset that will serve as the foundation for forthcoming Exploratory Data Analysis (EDA).

```
dataset = read.csv("BlackFriday.csv")
```

Next, proceed to import the essential libraries that shall constitute the backbone of analytical framework within this kernel.

```
if (!require(tidyverse)) {  
  install.packages("tidyverse", repos = "http://cran.us.r-project.org")  
}  
  
if (!require(scales)) {  
  install.packages("scales", repos = "http://cran.us.r-project.org")  
}  
  
if (!require(arules)) {  
  install.packages("arules", repos = "http://cran.us.r-project.org")  
}  
  
if (!require(gridExtra)) {  
  install.packages("gridExtra", repos = "http://cran.us.r-project.org")  
}  
  
if (!require(purrr)) {  
  install.packages("purrr", repos = "http://cran.us.r-project.org")  
}  
  
if (!require(readr)) {  
  install.packages("readr", repos = "http://cran.us.r-project.org")  
}  
  
if (!require(tidyr)) {  
  install.packages("tidyr", repos = "http://cran.us.r-project.org")  
}  
  
if (!require(dplyr)) {  
  install.packages("dplyr", repos = "http://cran.us.r-project.org")  
}  
  
if (!require(arulesViz)) {  
  install.packages("arulesViz", repos = "http://cran.us.r-project.org")  
}  
  
library(tidyverse)  
library(scales)  
library(arules)  
library(gridExtra)  
library(purrr)  
library(readr)
```

```
library(tidyr)
library(dplyr)
```

For the purpose of visualizing and delving into dataset, harness the capabilities of the “*tidyverse*” package. This package is renowned for its user-friendly syntax and an extensive array of valuable functions. To further enhance the visual representation of plots, also enlist the “*scales*” package, facilitating tailored adjustments to plot axes. In the culminating phase of this kernel, the “*arules*” package will come to the fore, playing an integral role in Association Rule Learning and the Apriori algorithm.

Comprehensive information pertaining to all the packages integrated into this EDA can be found in the Works Cited section of this kernel. Now, let us embark upon journey with an initial high-level overview of the entirety of the dataset.

```
summary(dataset)
```

```
##      User_ID      Product_ID      Gender      Age
## Min.   :1000001 Length:537577 Length:537577 Length:537577
## 1st Qu.:1001495 Class :character Class :character Class :character
## Median :1003031 Mode  :character Mode  :character Mode  :character
## Mean   :1002992
## 3rd Qu.:1004417
## Max.   :1006040
##
##      Occupation      City_Category      Stay_In_Current_City_Years
## Min.   : 0.000 Length:537577 Length:537577
## 1st Qu.: 2.000 Class :character Class :character
## Median : 7.000 Mode  :character Mode  :character
## Mean   : 8.083
## 3rd Qu.:14.000
## Max.   :20.000
##
##      Marital_Status      Product_Category_1      Product_Category_2      Product_Category_3
## Min.   :0.0000 Min.   : 1.000 Min.   : 2.00 Min.   : 3.0
## 1st Qu.:0.0000 1st Qu.: 1.000 1st Qu.: 5.00 1st Qu.: 9.0
## Median :0.0000 Median : 5.000 Median : 9.00 Median :14.0
## Mean   :0.4088 Mean   : 5.296 Mean   : 9.84 Mean   :12.7
## 3rd Qu.:1.0000 3rd Qu.: 8.000 3rd Qu.:15.00 3rd Qu.:16.0
## Max.   :1.0000 Max.   :18.000 Max.   :18.00 Max.   :18.0
##                                     NA's   :166986 NA's   :373299
##
##      Purchase
## Min.   : 185
## 1st Qu.: 5866
## Median : 8062
## Mean   : 9334
## 3rd Qu.:12073
## Max.   :23961
##
```

```
head(dataset)
```

```
##      User_ID Product_ID Gender      Age Occupation City_Category
## 1 1000001 P00069042      F 0-17      10      A
```

##	2	1000001	P00248942	F	0-17	10	A
##	3	1000001	P00087842	F	0-17	10	A
##	4	1000001	P00085442	F	0-17	10	A
##	5	1000002	P00285442	M	55+	16	C
##	6	1000003	P00193542	M	26-35	15	A
##		Stay_In_Current_City_Years	Marital_Status			Product_Category_1	
##	1		2			0	3
##	2		2			0	1
##	3		2			0	12
##	4		2			0	12
##	5		4+			0	8
##	6		3			0	1
##		Product_Category_2	Product_Category_3			Purchase	
##	1		NA		NA	8370	
##	2		6		14	15200	
##	3		NA		NA	1422	
##	4		14		NA	1057	
##	5		NA		NA	7969	
##	6		2		NA	15227	

Dataset reveals a total of 12 distinct columns, with each column aligning itself with a corresponding variable outlined below.

1. **User_ID:** Unique identifier of shopper.
2. **Product_ID:** Unique identifier of product. (No key given)
3. **Gender:** Sex of shopper.
4. **Age:** Age of shopper split into bins.
5. **Occupation:** Occupation of shopper. (No key given)
6. **City_Category:** Residence location of shopper. (No key given)
7. **Stay_In_Current_City_Years:** Number of years stay in current city.
8. **Marital_Status:** Marital status of shopper.
9. **Product_Category_1:** Product category of purchase.
10. **Product_Category_2:** Product may belong to other category.
11. **Product_Category_3:** Product may belong to other category.
12. **Purchase:** Purchase amount in dollars.

Upon perusing the initial rows of dataset, a distinctive pattern emerges:

1. Each row encapsulates a discrete transaction, signifying an individual item procured by a specific customer.
2. As an analysis advances, this delineation will assume paramount significance when aggregate transactions based on “*User_ID*”, culminating in an aggregation of purchases attributed to each unique customer.

A notable critique pertinent to this dataset pertains to the absence of a definitive key that correlates various “*Product_IDs*” with their corresponding item descriptions. This lack of explicit linkage (for instance, an inability to seamlessly correlate P00265242 with a readily identifiable item) potentially poses a challenge.

In a real-world context, the ideal scenario would involve a supplementary dataset furnishing comprehensive information, coupling item names with their respective “*Product_IDs*”. The integration of supplementary data, although not directly affecting Exploratory Data Analysis (EDA), would significantly improve the effectiveness of the Apriori algorithm implementation and contribute to a clearer interpretation of specific aspects within EDA.

2.1.2 Gender

Initiating exploratory journey, initial focal point shall be the examination of the gender distribution among shoppers frequenting this establishment. Given that each row corresponds to a distinct transaction, a preliminary step entails grouping the data by “*User_ID*” to eliminate any duplicate entries. This process will serve to streamline the analysis and facilitate an accurate portrayal of the gender distribution within the shopper demographic.

```
dataset_gender = dataset %>%  
  select(User_ID, Gender) %>%  
  group_by(User_ID) %>%  
  distinct()  
  
head(dataset_gender)
```

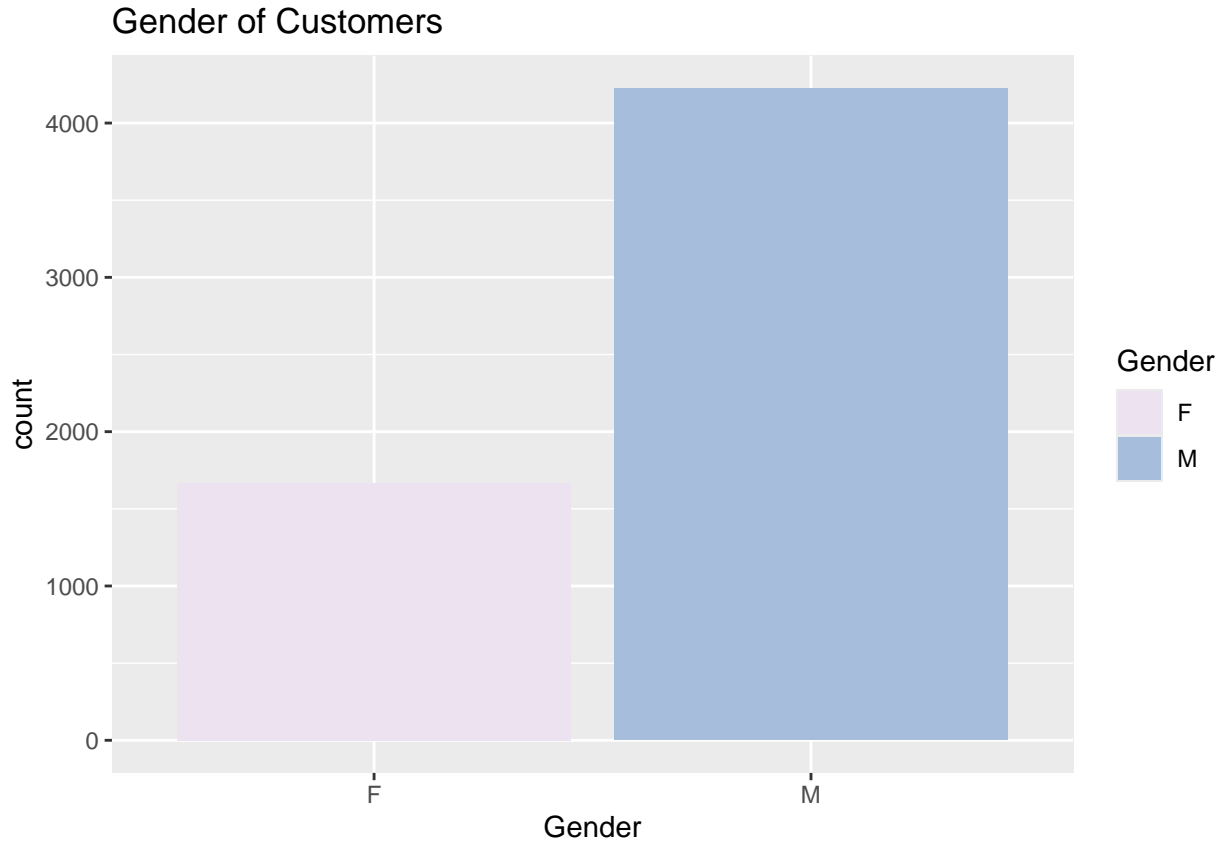
```
## # A tibble: 6 x 2  
## # Groups:   User_ID [6]  
##   User_ID Gender  
##   <int> <chr>  
## 1 1000001 F  
## 2 1000002 M  
## 3 1000003 M  
## 4 1000004 M  
## 5 1000005 M  
## 6 1000006 F
```

```
summary(dataset_gender$Gender)
```

```
##   Length      Class      Mode  
##   5891 character character
```

With the requisite dataframe in place, encapsulating the correlation between each “*User_ID*” and their associated gender, coupled with the comprehensive counts for reference, primed to depict the gender distribution across dataset through an illustrative plot.

```
options(scipen=10000) # To remove scientific numbering  
  
genderDist = ggplot(data = dataset_gender) +  
  geom_bar(mapping = aes(x = Gender, y = ..count.., fill = Gender)) +  
  labs(title = 'Gender of Customers') +  
  scale_fill_brewer(palette = 'PuBuGn')  
print(genderDist)
```



Evidently, the male demographic significantly outweighs the female counterpart in terms of shopping participation on Black Friday within store. This gender distribution metric assumes particular significance for retailers, as it can potentially steer decisions regarding store layout, product assortment, and other variables, contingent upon the proportion of male and female shoppers.

2.1.3 Purchases between Female and Male shoppers

Citing a research study from the Clothing and Textiles Research Journal, it is revealed that certain factors such as involvement, variety seeking, and the physical store environment are antecedents of shopping experience satisfaction. The study further suggests the mediating role of hedonic shopping value in shopping satisfaction, a correlation confirmed among female subjects, yet not among male respondents. While this may not yield immediate prescriptive insights for retail establishments, it underscores a gender-based disparity in the derived value of shopping and its nexus with gender, serving as a compelling consideration for retailers.

To delve deeper into analysis, let us proceed to compute the average spending amount in relation to gender. To facilitate interpretability and traceability, construct distinct tables before ultimately merging them for a holistic perspective.

```
total_purchase_user = dataset %>%
  select(User_ID, Gender, Purchase) %>%
  group_by(User_ID) %>%
  arrange(User_ID) %>%
  summarise(Total_Purchase = sum(Purchase))

user_gender = dataset %>%
```

```
select(User_ID, Gender) %>%
  group_by(User_ID) %>%
  arrange(User_ID) %>%
  distinct()
```

```
head(user_gender)
```

```
## # A tibble: 6 x 2
## # Groups:   User_ID [6]
##   User_ID Gender
##   <int> <chr>
## 1 1000001 F
## 2 1000002 M
## 3 1000003 M
## 4 1000004 M
## 5 1000005 M
## 6 1000006 F
```

```
head(total_purchase_user)
```

```
## # A tibble: 6 x 2
##   User_ID Total_Purchase
##   <int>         <int>
## 1 1000001         333481
## 2 1000002         810353
## 3 1000003         341635
## 4 1000004         205987
## 5 1000005         821001
## 6 1000006         379450
```

```
user_purchase_gender = full_join(total_purchase_user, user_gender, by = "User_ID")
head(user_purchase_gender)
```

```
## # A tibble: 6 x 3
##   User_ID Total_Purchase Gender
##   <int>         <int> <chr>
## 1 1000001         333481 F
## 2 1000002         810353 M
## 3 1000003         341635 M
## 4 1000004         205987 M
## 5 1000005         821001 M
## 6 1000006         379450 F
```

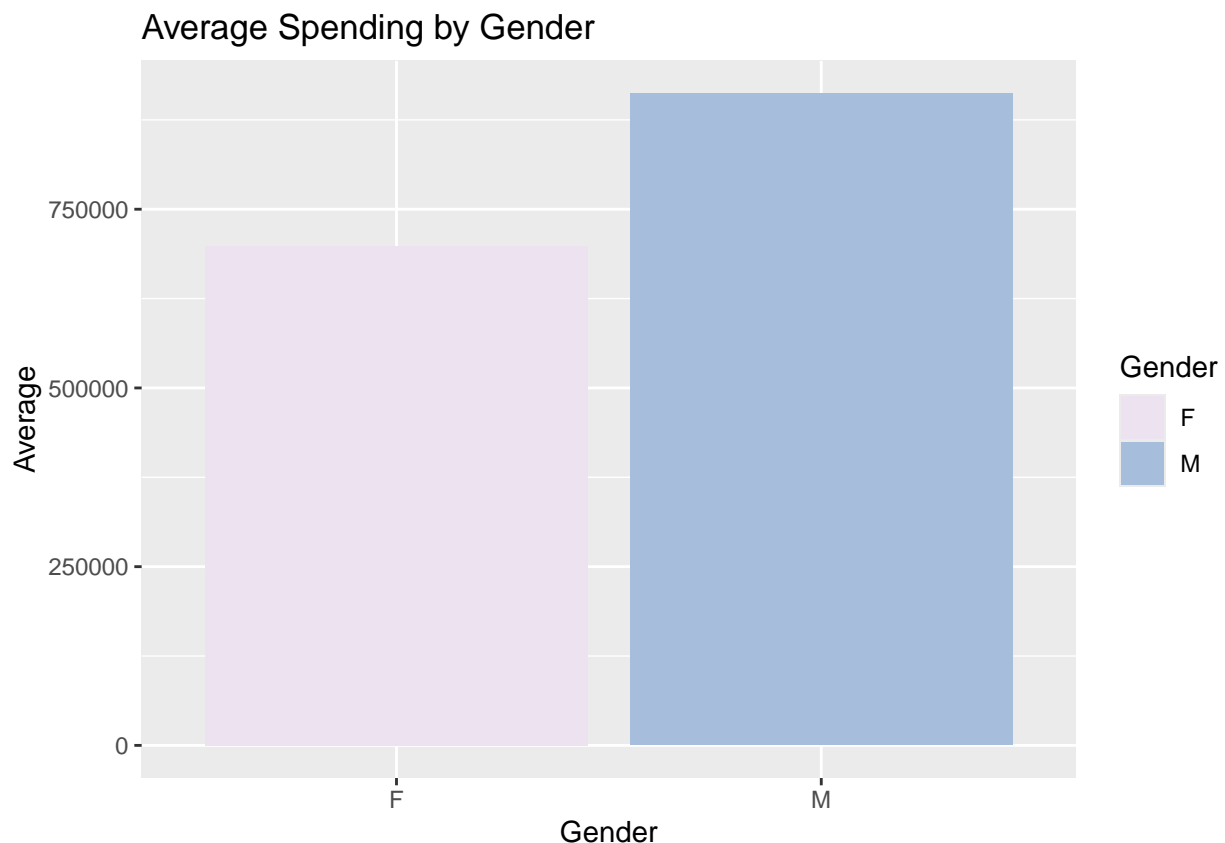
```
average_spending_gender = user_purchase_gender %>%
  group_by(Gender) %>%
  summarize(Purchase = sum(as.numeric(Total_Purchase)),
    Count = n(),
    Average = Purchase/Count)
head(average_spending_gender)
```

```
## # A tibble: 2 x 4
```

```
##   Gender   Purchase Count Average
##   <chr>      <dbl> <int>   <dbl>
## 1 F         1164624021 1666 699054.
## 2 M         3853044357 4225 911963.
```

The calculated averages indicate that the average transaction amount for females stood at 699,054, whereas for males, it reached 911,963. To provide a visual representation of findings, let us proceed to create a visual depiction of these results.

```
genderAverage = ggplot(data = average_spending_gender) +
  geom_bar(mapping = aes(x = Gender, y = Average,
                        fill = Gender), stat = 'identity') +
  labs(title = 'Average Spending by Gender') +
  scale_fill_brewer(palette = 'PuBuGn')
print(genderAverage)
```



A compelling observation comes to light through visualization. Despite the relative disparity in the frequency of purchases between female and male shoppers within this particular store, the average transaction amount for females is remarkably close to that of their male counterparts.

It is imperative to exercise caution in interpreting these results, recognizing the need to consider the scale of these expenditures. While females are nearly matching the average spending of males, it's important to underscore that, on average, their expenditures are still approximately 250,000 units lower than those of males. This insight underscores the significance of contextualizing the data within a broader framework.

2.1.4 Top Sellers

Transitioning focus, let us now embark on an exploration of best-performing products. In this context, forego the grouping of data by product ID, as intention is to retain duplicate entries. This approach ensures a comprehensive examination, accounting for scenarios where customers procure multiple quantities of the same product.

```
top_sellers = dataset %>%
  count(Product_ID, sort = TRUE)

top_5 = head(top_sellers, 5)

top_5
```

```
##   Product_ID    n
## 1  P00265242 1858
## 2  P00110742 1591
## 3  P00025442 1586
## 4  P00112142 1539
## 5  P00057642 1430
```

Looks like top 5 best sellers are (by product ID):

1. P00265242 = 1858
2. P00110742 = 1591
3. P00025442 = 1586
4. P00112142 = 1539
5. P00057642 = 1430

Having successfully identified the top 5 best-selling products, trajectory leads us to a closer examination of the best-performing individual product, denoted as P00265242. This granular analysis aims to provide a more comprehensive understanding of the specific attributes and dynamics that contribute to the exceptional sales performance of this particular product.

```
best_seller = dataset[dataset$Product_ID == 'P00265242', ]

head(best_seller)
```

```
##      User_ID Product_ID Gender   Age Occupation City_Category
## 400  1000066  P00265242     M 26-35         18             C
## 1192 1000196  P00265242     F 36-45          9             C
## 1373 1000222  P00265242     M 26-35          1             A
## 1846 1000301  P00265242     M 18-25          4             B
## 2210 1000345  P00265242     M 26-35         12             A
## 2405 1000383  P00265242     F 26-35          7             A
##      Stay_In_Current_City_Years Marital_Status Product_Category_1
## 400                2                0                5
## 1192               4+                0                5
## 1373                1                0                5
```

## 1846	4+	0	5
## 2210	2	1	5
## 2405	4+	1	5
##	Product_Category_2	Product_Category_3	Purchase
## 400	8	NA	8652
## 1192	8	NA	8767
## 1373	8	NA	6944
## 1846	8	NA	8628
## 2210	8	NA	8593
## 2405	8	NA	6998

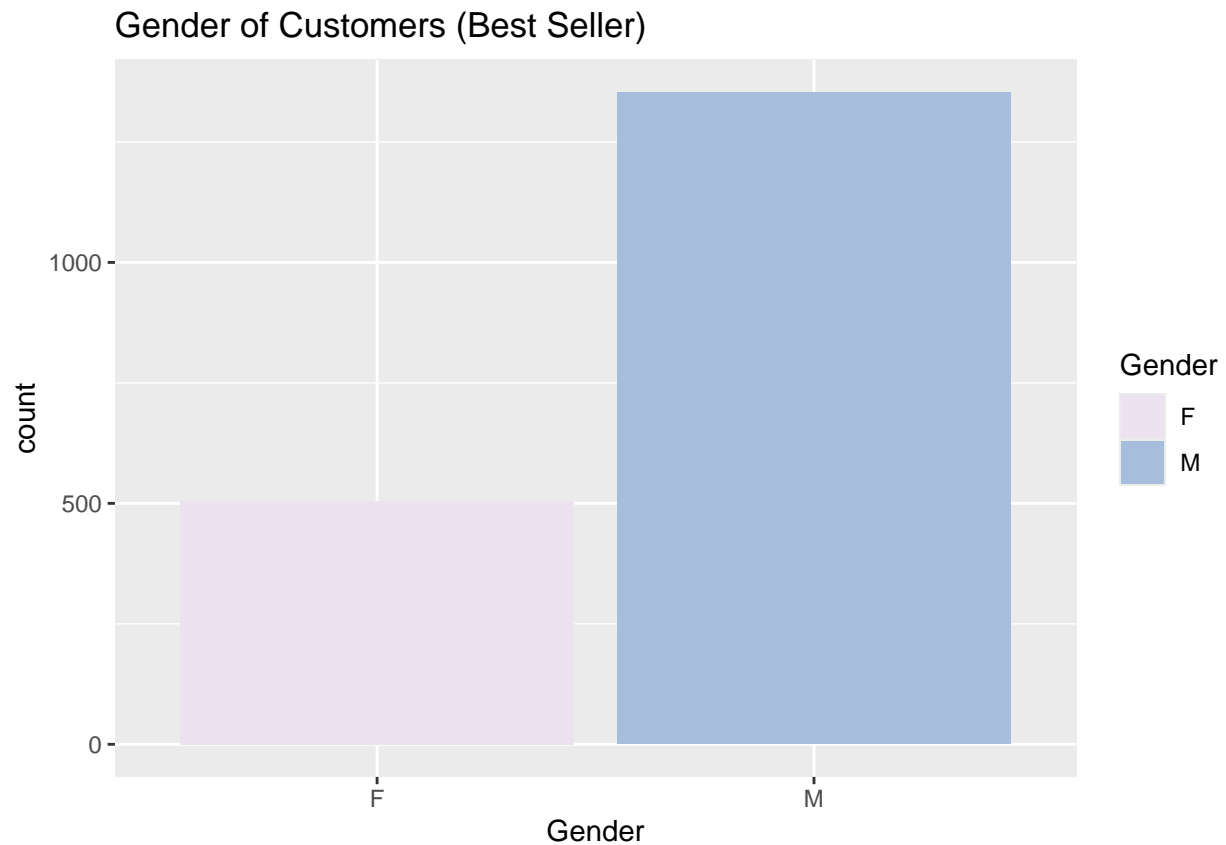
From analysis, it is evident that this particular product falls within the categorical indices of Product_Category_1 = 5 and Product_Category_2 = 8. As highlighted earlier, the absence of an explicit key detailing item names poses a limitation in identifying the precise nature of this product. An intriguing revelation surfaces as observe variations in the purchase prices of the same product across different customers.

This phenomenon could potentially be attributed to an array of factors, encompassing “*Black Friday*” promotions, discounts, or the utilization of distinct coupon codes. Alternatively, a deeper investigation may be warranted to unearth the underlying rationale for the disparities in purchase prices of an identical product among diverse customers.

2.1.5 Correlation between Gender and the Best Selling Product

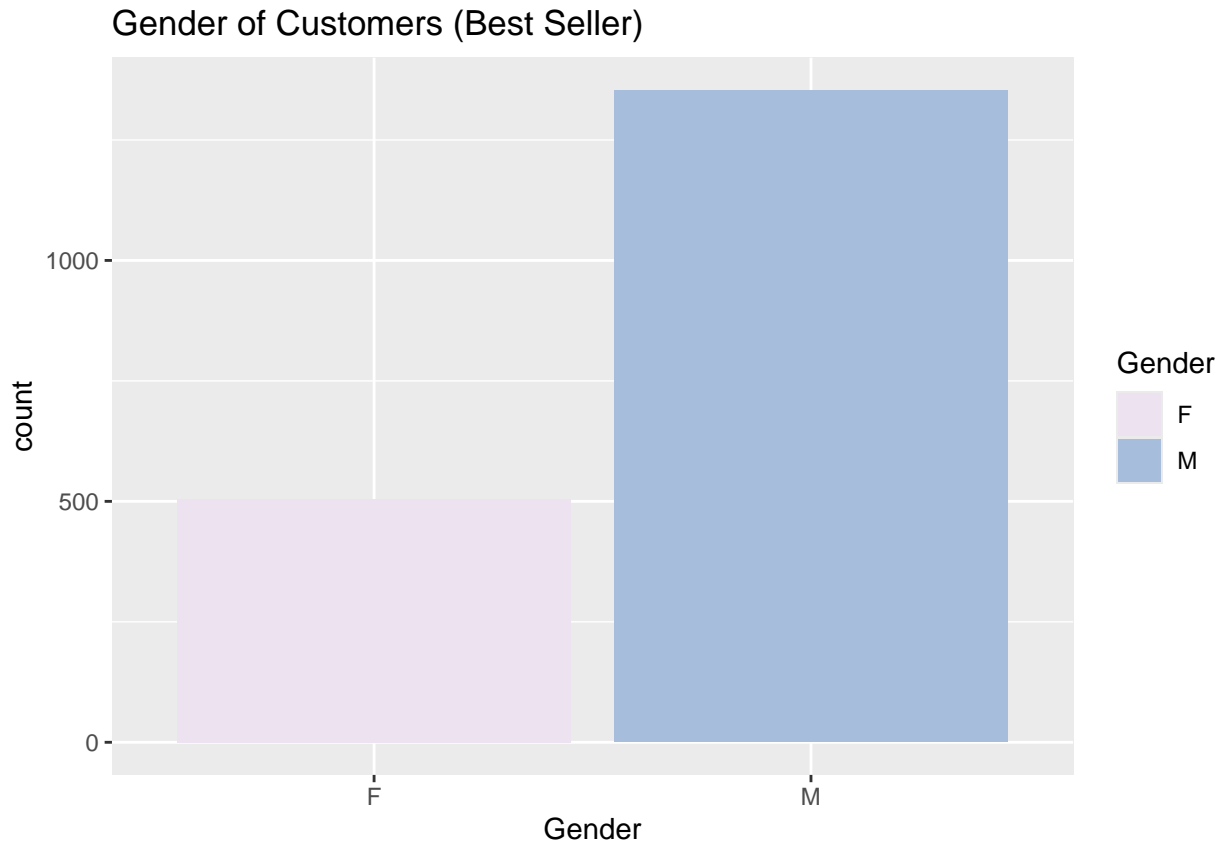
In pursuit of a comprehensive analysis, inquiry advances to ascertain if any discernible correlation between gender and the best-selling product, P00265242, is discernible.

```
genderDist_bs = ggplot(data = best_seller) + geom_bar(mapping = aes(x = Gender,
  y = ..count.., fill = Gender)) +
  labs(title = 'Gender of Customers (Best Seller)') +
  scale_fill_brewer(palette = 'PuBuGn')
print(genderDist_bs)
```



A similar distribution between genders to overall dataset gender split - lets confirm.

```
genderDist_bs = ggplot(data = best_seller) +  
  geom_bar(mapping = aes(x = Gender, y = ..count.., fill = Gender)) +  
  labs(title = 'Gender of Customers (Best Seller)') +  
  scale_fill_brewer(palette = 'PuBuGn')  
  
print(genderDist_bs)
```



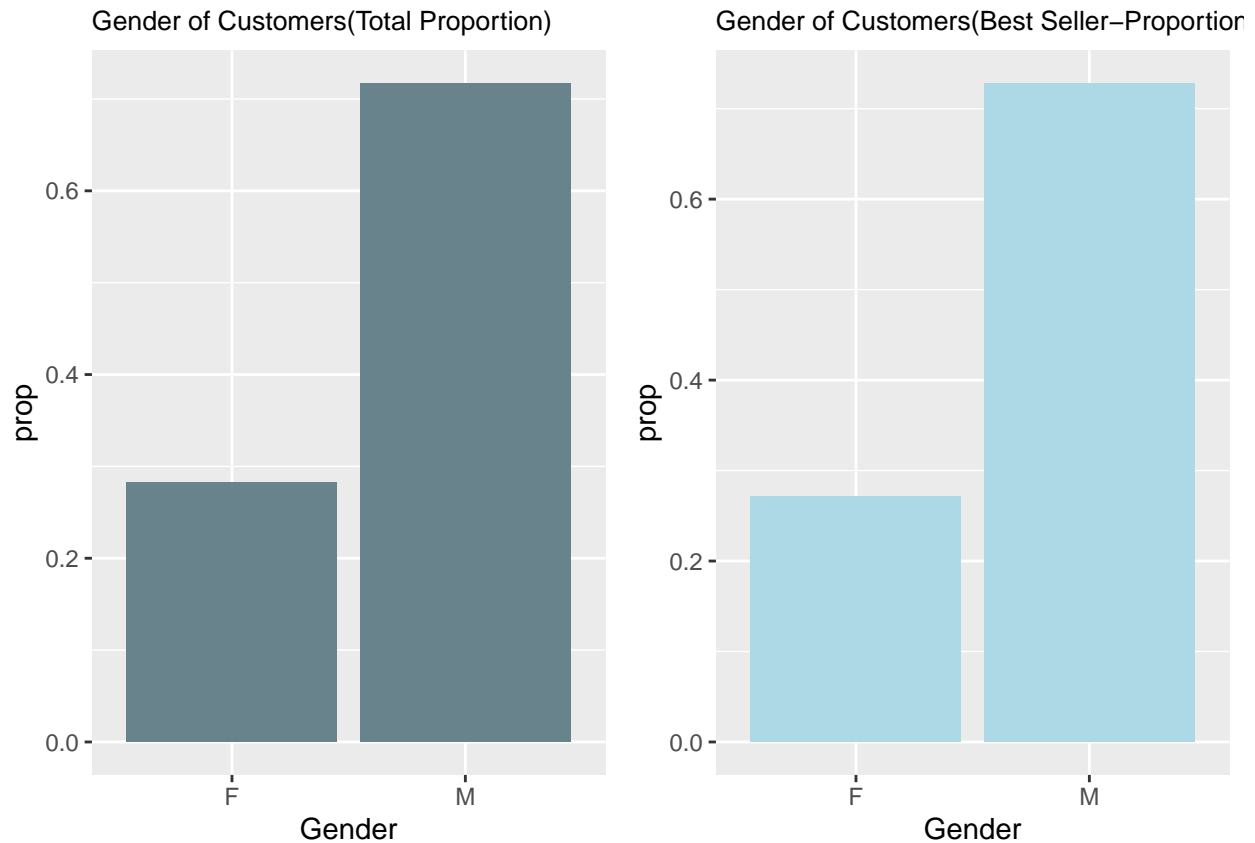
Upon a comprehensive review of the aggregate dataset, it is apparent that both the purchasers of the best-selling product and the purchasers of all products collectively exhibit a relatively balanced gender distribution, with approximately 25% representing females and 75% representing males.

Although a subtle disparity is discernible, the overarching inference suggests that best-selling product does not distinctly cater to a particular gender demographic. Transitioning to the examination of the Age variable, analytically trajectory proceeds. A similar distribution between genders to overall dataset gender split - lets confirm.

```
genderDist_bs_prop = ggplot(data = best_seller) +
  geom_bar(fill = 'lightblue', mapping = aes(x = Gender,
    y = ..prop.., group = 1, fill = Gender)) +
  labs(title = 'Gender of Customers(Best Seller-Proportion)') +
  theme(plot.title = element_text(size=9.5))

genderDist_prop = ggplot(data = dataset_gender) +
  geom_bar(fill = "lightblue4", mapping = aes(x = Gender,
    y = ..prop.., group = 1)) +
  labs(title = 'Gender of Customers(Total Proportion)') +
  theme(plot.title = element_text(size=9.5))

grid.arrange(genderDist_prop, genderDist_bs_prop, ncol=2)
```

2.1.6 Age

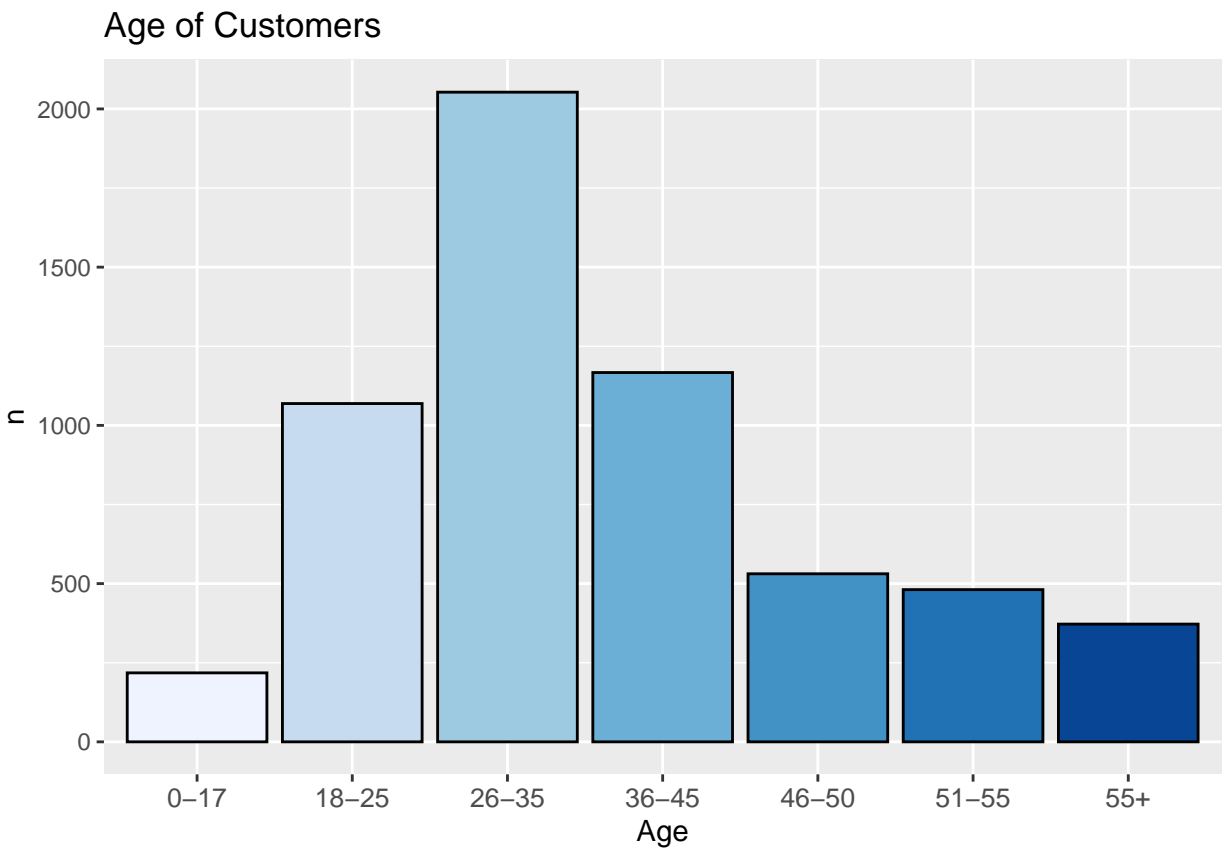
Certainly, let's delve into the analysis of the Age variable step by step. First, create a table that tabulates the count of customers in each age category based on the provided dataset:

```
customers_age = dataset %>%
  select(User_ID, Age) %>%
  distinct() %>%
  count(Age)
customers_age
```

```
##      Age      n
## 1  0-17    218
## 2 18-25   1069
## 3 26-35   2053
## 4 36-45   1167
## 5 46-50    531
## 6 51-55    481
## 7  55+    372
```

Afterward, visualize this distribution using a bar plot:

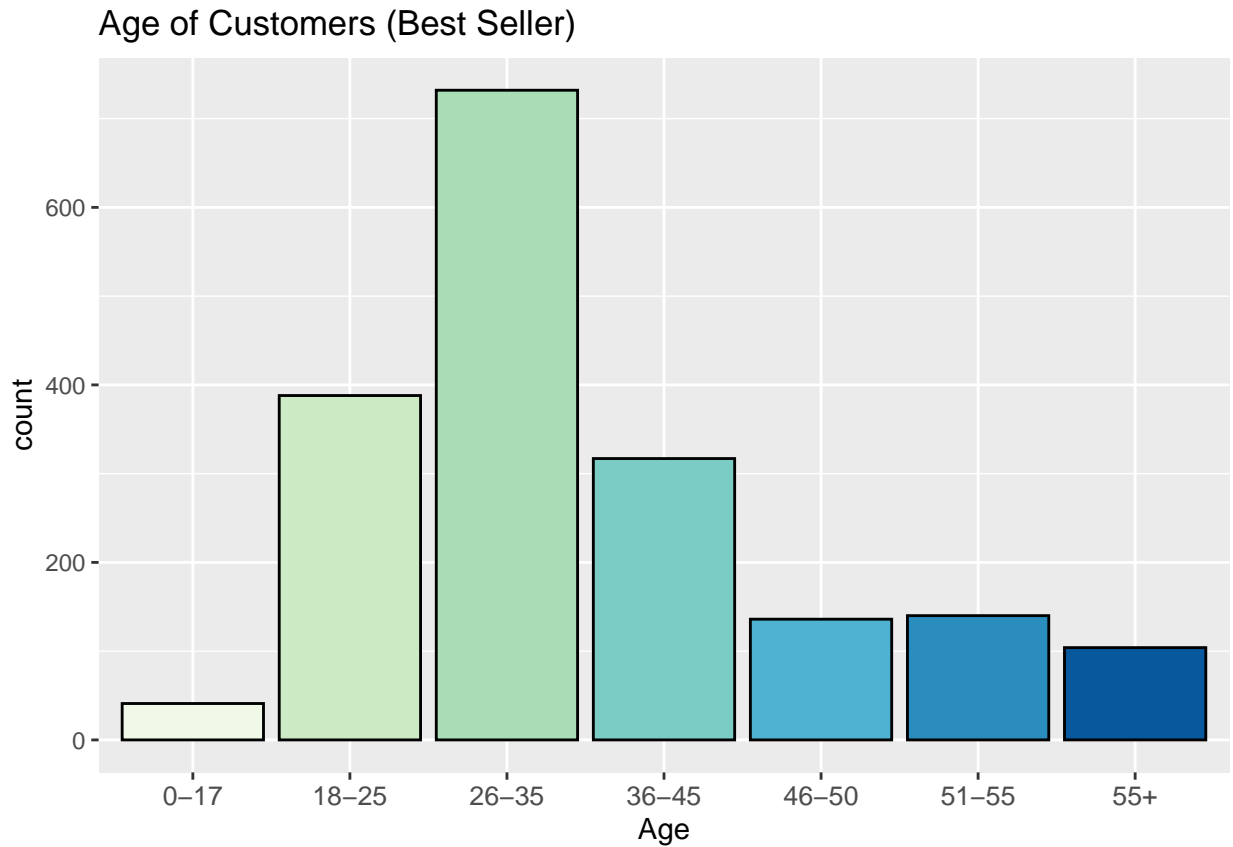
```
customers_age_vis = ggplot(data = customers_age) +
  geom_bar(color = 'black', stat = 'identity',
    mapping = aes(x = Age, y = n, fill = Age)) +
  labs(title = 'Age of Customers') +
  theme(axis.text.x = element_text(size = 10)) +
  scale_fill_brewer(palette = 'Blues') +
  theme(legend.position="none")
print(customers_age_vis)
```



2.1.7 Purchasing behavior of different Age groups

Further, create a similar chart depicting the age distribution specifically within the “*best seller*” category to identify any potential trends:

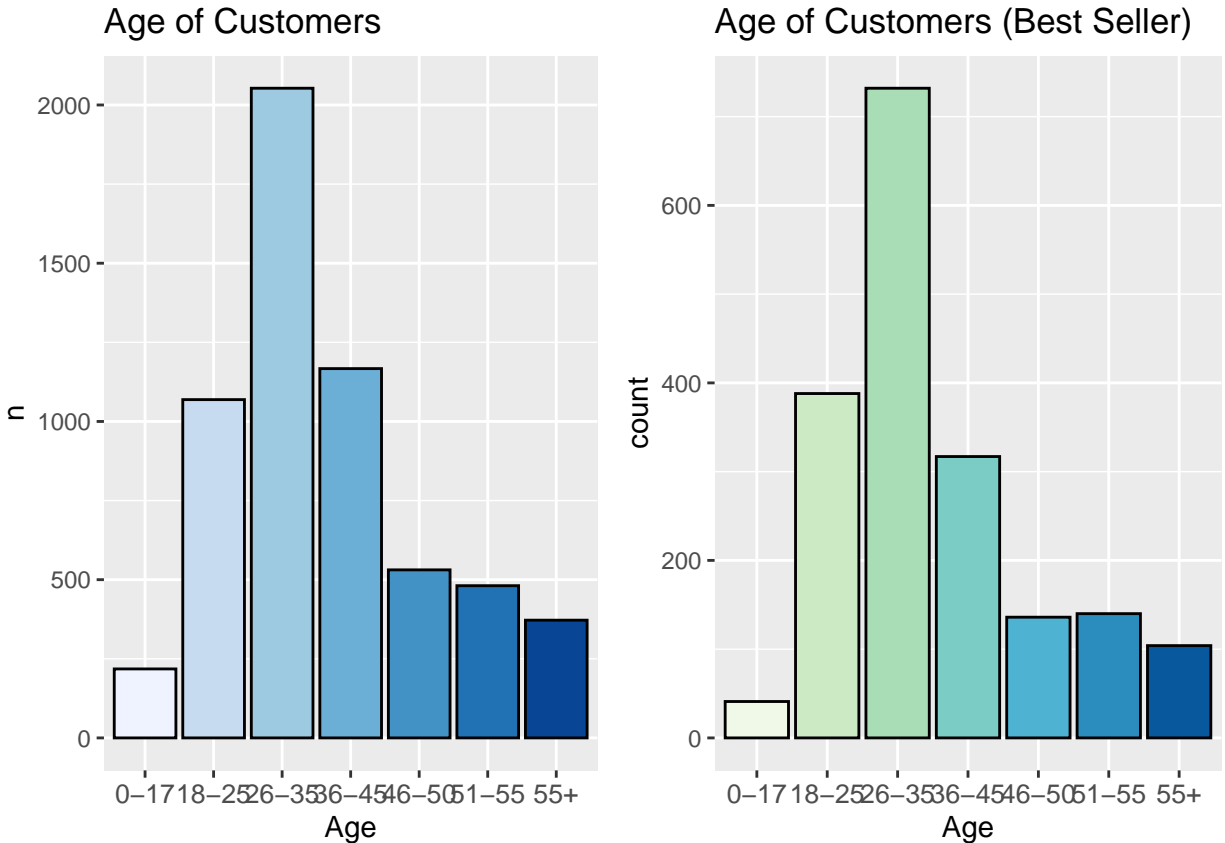
```
ageDist_bs = ggplot(data = best_seller) +
  geom_bar(color = 'black', mapping = aes(x = Age,
    y = ..count.., fill = Age)) +
  labs(title = 'Age of Customers (Best Seller)') +
  theme(axis.text.x = element_text(size = 10)) +
  scale_fill_brewer(palette = 'GnBu') +
  theme(legend.position="none")
print(ageDist_bs)
```



The visual analysis highlights that customers in the age groups of 18-25 and 26-35 constitute the majority of purchasers for the best-selling product. A comparison between the age distribution of the best-selling product and the overall dataset reveals some deviations.

Particularly, customers aged over 45 appear to be slightly less inclined to purchase the top-selling product compared to other products in the dataset.

```
grid.arrange(customers_age_vis, ageDist_bs, ncol=2)
```



This in-depth exploration of age provides valuable insights into the purchasing behavior of different age groups. As shift focus to another variable, quest for comprehensive analysis continues.

2.1.8 City

Certainly, can proceed by constructing a table that presents each “*User_ID*” alongside its corresponding “*City_Category*”. This will serve as a foundation step for subsequent analytical exploration, which will delve into the distribution of shoppers across different city categories. To achieve this, employ the following code:

```
customers_location = dataset %>%
  select(User_ID, City_Category) %>%
  distinct()
head(customers_location)
```

```
##   User_ID City_Category
## 1 1000001             A
## 2 1000002             C
## 3 1000003             A
## 4 1000004             B
## 5 1000005             A
## 6 1000006             A
```

This table will provide a comprehensive snapshot, pairing each distinct “*User_ID*” with its associated “*City_Category*”. This will serve as a starting point for us to uncover trends and insights related to shopping behavior based on geographical locations.

```
customers_location_vis = ggplot(data = customers_location) +
  geom_bar(color = 'white', mapping = aes(x = City_Category,
  y = ..count.., fill = City_Category)) +
  labs(title = 'Location of Customers') +
  scale_fill_brewer(palette = "Dark2") +
  theme(legend.position="none")
print(customers_location_vis)
```



Observation unveils that the majority of customers are residents of City C. Building upon this insight, proceed to calculate the total purchase amount attributed to each city category. This subsequent analysis aims to shed light on which city's customers have made the most substantial expenditures at store. To initiate this computation, can employ the following code:

```
purchases_city = dataset %>%
  group_by(City_Category) %>%
  summarise(Purchases = sum(Purchase))

purchases_city_1000s = purchases_city %>%
  mutate(purchasesThousands = purchases_city$Purchases / 1000)

purchases_city_1000s
```

```
## # A tibble: 3 x 3
##   City_Category Purchases purchasesThousands
##   <chr>          <int>          <dbl>
```

## 1 A	1295668797	1295669.
## 2 B	2083431612	2083432.
## 3 C	1638567969	1638568.

2.1.9 Shopping behaviors across different cities

In the interest of enhanced readability and charting, it's a commonplace practice to divide the values in the Purchases column by 1000. This pragmatic approach aligns with prevailing conventions in the business and accounting realms, rendering large numbers more accessible for interpretation and graphical representation. With the requisite table in place, next step involves visualizing the outcomes. To achieve this, can utilize the following code:

```
purchaseCity_vis = ggplot(data = purchases_city_1000s, aes(x = City_Category,
  y = purchasesThousands, fill = City_Category)) +
  geom_bar(color = 'white', stat = 'identity') +
  labs(title = 'Total Customer Purchase Amount (by City)',
  y = '($000s)', x = 'City Category') +
  scale_fill_brewer(palette = "Dark2") +
  theme(legend.position="none",
  plot.title = element_text(size = 9))
print(purchaseCity_vis)
```



```
grid.arrange(customers_location_vis, purchaseCity_vis, ncol=2)
```



The visualization effectively portrays the shopping dynamics on Black Friday, indicating that City C exhibited the highest shopper frequency at store, while City B surpassed others in terms of total purchase amounts. To further decipher the rationale behind this trend, exploration continues. To assess the number of purchases made by customers from each city, initiate by calculating the total number of purchases corresponding to each “*User_ID*”. The following code accomplishes this:

```
customers = dataset %>%
  group_by(User_ID) %>%
  count(User_ID)
head(customers)
```

```
## # A tibble: 6 x 2
## # Groups:   User_ID [6]
##   User_ID     n
##   <int> <int>
## 1 1000001    34
## 2 1000002    76
## 3 1000003    29
## 4 1000004    13
## 5 1000005   106
## 6 1000006    46
```

This code snippet will yield a table that encapsulates the total number of purchases associated with each unique “*User_ID*”. Subsequently, can proceed to extract meaningful insights from this data, shedding light on the shopping behaviors across different cities.

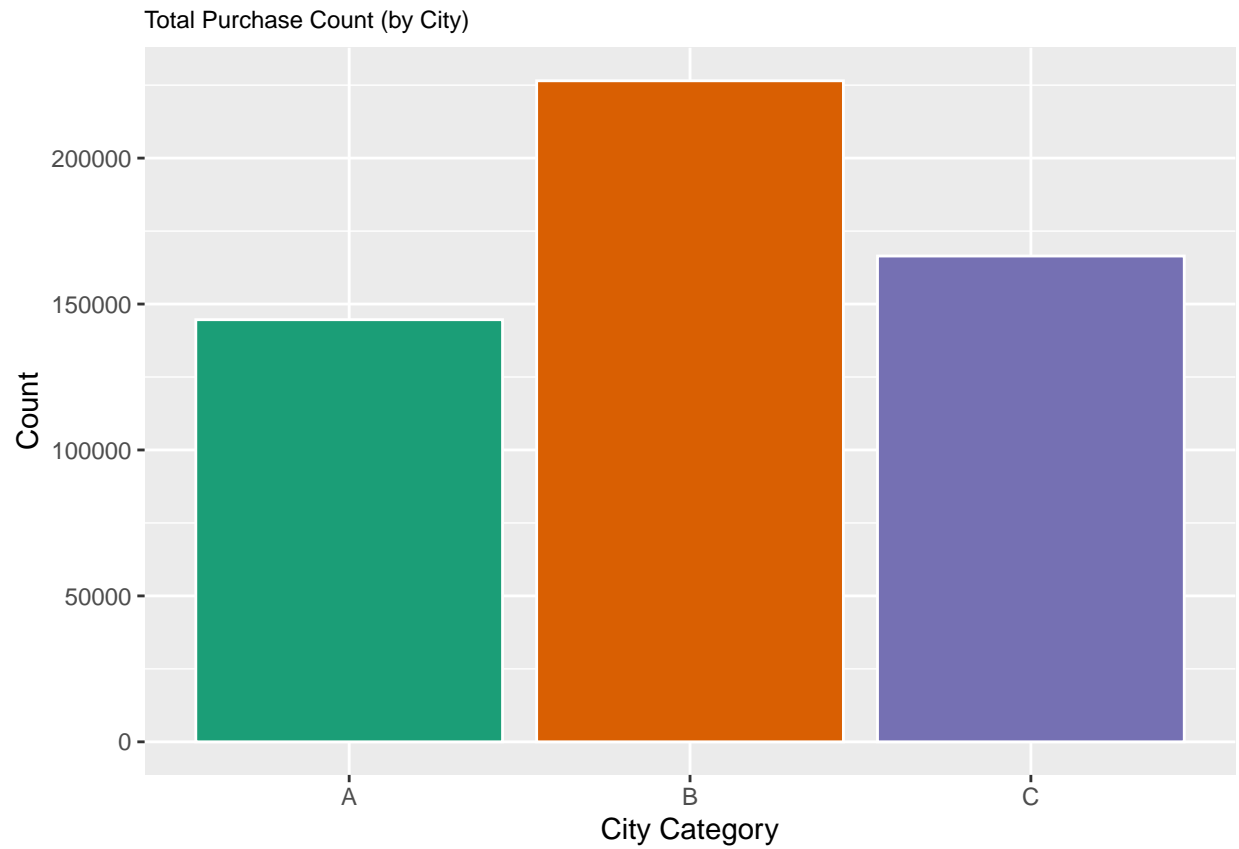
```
customers_City = dataset %>%
  select(User_ID, City_Category) %>%
  group_by(User_ID) %>%
  distinct() %>%
  ungroup() %>%
  left_join(customers, customers_City, by = 'User_ID')
head(customers_City)
```

```
## # A tibble: 6 x 3
##   User_ID City_Category     n
##   <int> <chr>         <int>
## 1 1000001 A             34
## 2 1000002 C             76
## 3 1000003 A             29
## 4 1000004 B             13
## 5 1000005 A            106
## 6 1000006 A             46
```

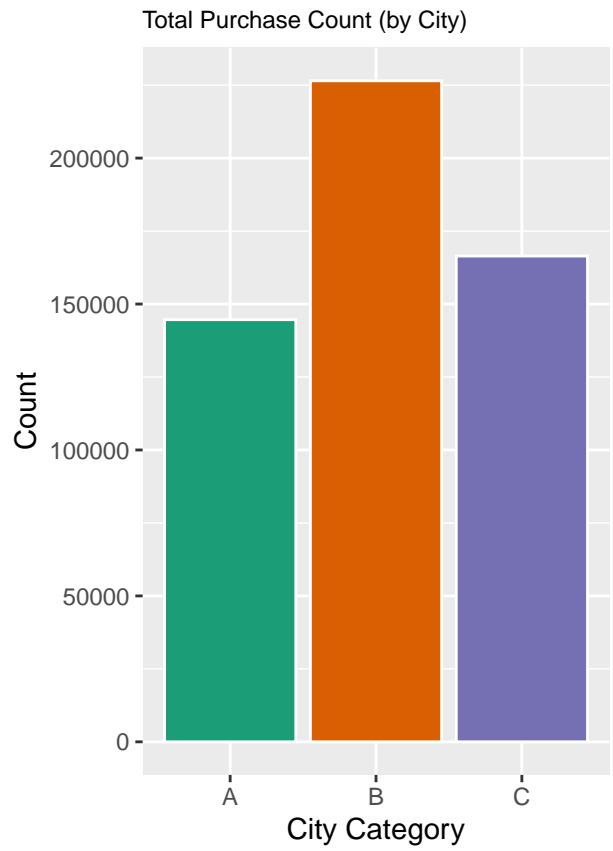
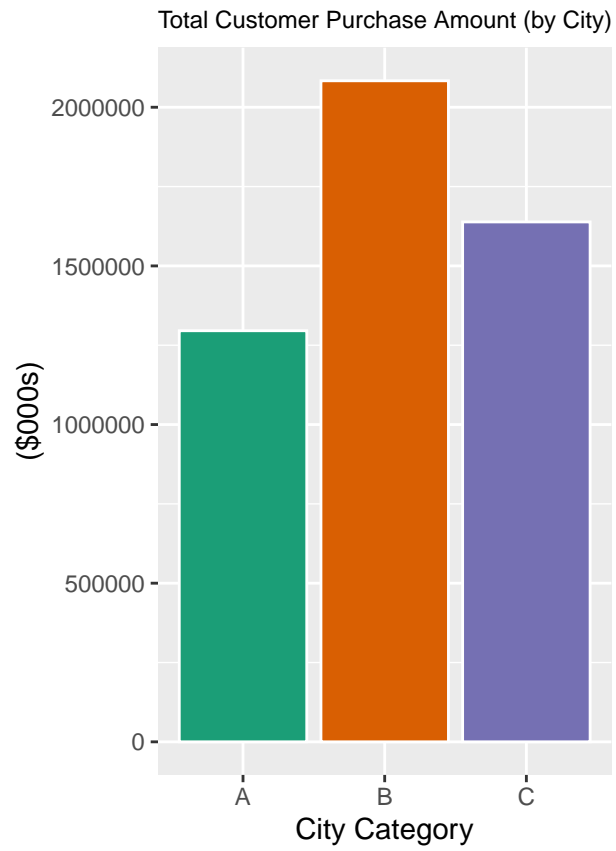
```
city_purchases_count = customers_City %>%
  select(City_Category, n) %>%
  group_by(City_Category) %>%
  summarise(CountOfPurchases = sum(n))
city_purchases_count
```

```
## # A tibble: 3 x 2
##   City_Category CountOfPurchases
##   <chr>         <int>
## 1 A             144638
## 2 B             226493
## 3 C             166446
```

```
city_count_purchases_vis = ggplot(data = city_purchases_count,
  aes(x = City_Category, y = CountOfPurchases, fill =
    City_Category)) + geom_bar(color = 'white',
  stat = 'identity') + labs(title =
  'Total Purchase Count (by City)',
  y = 'Count', x = 'City Category') +
  scale_fill_brewer(palette = "Dark2") +
  theme(legend.position="none",
    plot.title = element_text(size = 9))
print(city_count_purchases_vis)
```

```
grid.arrange(purchaseCity_vis, city_count_purchases_vis, ncol = 2)
```



3 Chapter 3

3.1 Results and Discussion

The similarity in the distribution patterns between the “*Total Count of Purchases*” chart and the “*Total Customer Purchase Amount*” chart indeed implies that customers from City B are making a higher number of purchases rather than opting for more expensive products.

This insight gains traction from the observation that if the case were otherwise, where customers from City B bought more expensive products, likely encounter a scenario where a lower count of purchases correlates with a higher total purchase amount.

Having established this insight, proceed to the subsequent phase of the analysis. Given that the purchase counts across different “*City_Category*” segments mirror the distribution patterns of the total purchase amount, inquiry pivots to an examination of the distribution of best-selling product (P00265242) within each “*City_Category*”. This examination will potentially unveil nuanced trends or preferences specific to different city categories.

```
head(best_seller)
```

```
##      User_ID Product_ID Gender   Age Occupation City_Category
## 400  1000066  P00265242      M 26-35         18             C
## 1192 1000196  P00265242      F 36-45          9             C
## 1373 1000222  P00265242      M 26-35          1             A
## 1846 1000301  P00265242      M 18-25          4             B
## 2210 1000345  P00265242      M 26-35         12             A
## 2405 1000383  P00265242      F 26-35          7             A
##      Stay_In_Current_City_Years Marital_Status Product_Category_1
## 400                             2                0                5
## 1192                            4+                0                5
## 1373                             1                0                5
## 1846                            4+                0                5
## 2210                             2                1                5
## 2405                            4+                1                5
##      Product_Category_2 Product_Category_3 Purchase
## 400                     8                NA      8652
## 1192                     8                NA      8767
## 1373                     8                NA      6944
## 1846                     8                NA      8628
## 2210                     8                NA      8593
## 2405                     8                NA      6998
```

```
best_seller_city = best_seller %>%
  select(User_ID, City_Category) %>%
  distinct() %>%
  count(City_Category)
best_seller_city
```

```
##   City_Category    n
## 1              A 396
## 2              B 626
## 3              C 836
```

```
best_seller_city_vis = ggplot(data = best_seller_city, aes(x = City_Category,
y = n, fill = City_Category)) +
  geom_bar(color = 'white', stat = 'identity') +
  labs(title = 'Best Seller Purchase Count (by City)',
y = 'Count', x = 'City_Category') +
  scale_fill_brewer(palette = "Blues") +
  theme(legend.position="none", plot.title =
    element_text(size = 9))
grid.arrange(city_count_purchases_vis, best_seller_city_vis, ncol = 2)
```



Indeed, observation is quite intriguing and sheds light on the intricate nuances of customer behavior. While customers from City C exhibit a higher propensity to purchase the best-selling product (P00265242) compared to residents of City A and City B, the overall purchase count from City C lags behind that of City B.

This intriguing contrast underscores the complexity of shopping behaviors across different city categories. It implies that although City C residents are particularly inclined to purchase the best-selling product, they may not be as prolific in terms of making overall purchases when compared to City B residents. This revelation underscores the importance of comprehensive analysis in uncovering subtle trends and patterns that may not be immediately evident. As shift focus to another variable, the journey of exploration continues.

3.1.1 Stay in Current City

Certainly, can proceed by examining the distribution of customers who have resided in their respective cities for the longest duration. This exploration will provide insights into the longevity of customer relation-

ships with their residing cities, potentially offering valuable insights into shopping behaviors and patterns influenced by the length of city residence. To commence this analysis, can employ the following code:

```
customers_stay = dataset %>%
  select(User_ID, City_Category, Stay_In_Current_City_Years) %>%
  group_by(User_ID) %>%
  distinct()
head(customers_stay)
```

```
## # A tibble: 6 x 3
## # Groups:   User_ID [6]
##   User_ID City_Category Stay_In_Current_City_Years
##   <int> <chr>         <chr>
## 1 1000001 A             2
## 2 1000002 C             4+
## 3 1000003 A             3
## 4 1000004 B             2
## 5 1000005 A             1
## 6 1000006 A             1
```

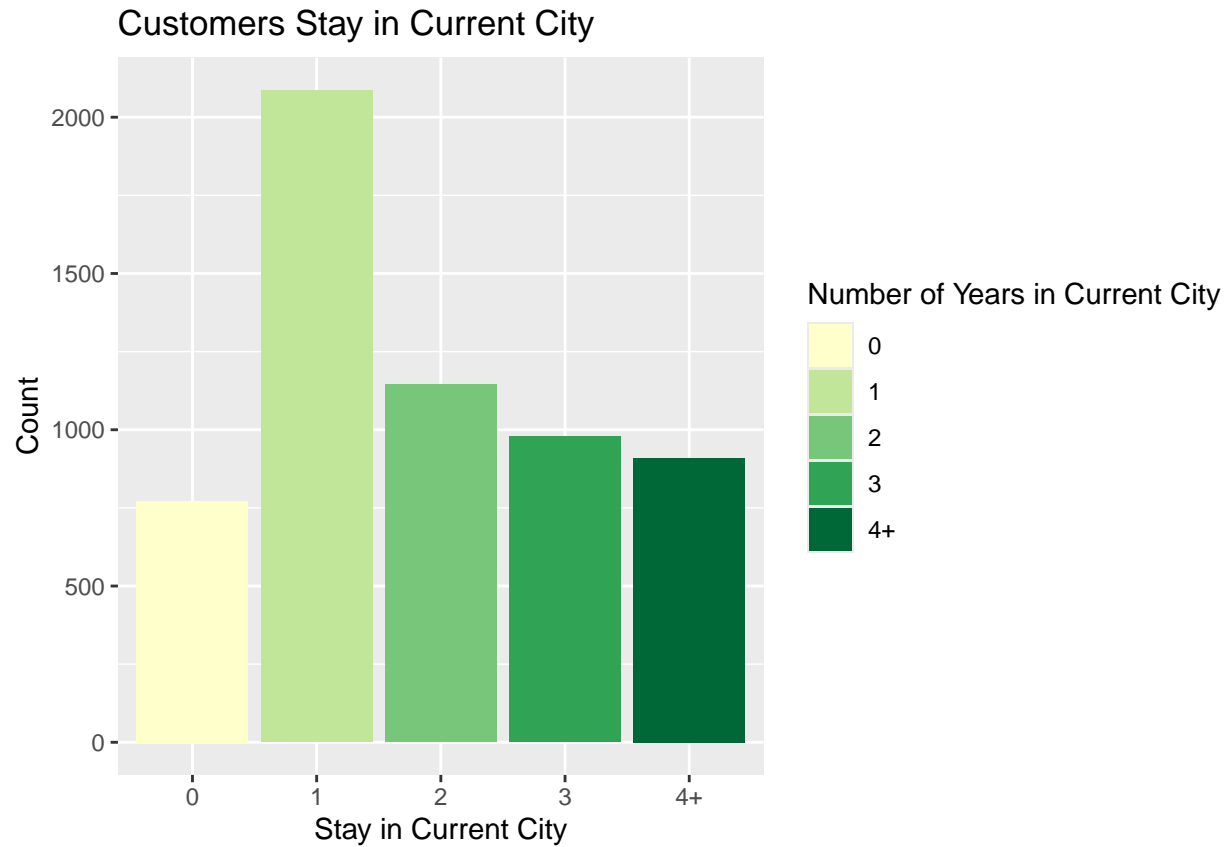
Now that dataset in order, plot and explore. Lets see where most of customers are living. This code will generate a table that encapsulates the total number of purchases for each unique “*User_ID*”, categorized by the duration of their stay in their current city. Subsequently, analysis can delve into this data to reveal trends and patterns that might emerge from the distribution of customers’ residence duration.

```
residence = customers_stay %>%
  group_by(City_Category) %>%
  tally()
head(residence)
```

```
## # A tibble: 3 x 2
##   City_Category      n
##   <chr>         <int>
## 1 A             1045
## 2 B             1707
## 3 C             3139
```

Looks like most of customers are living in City C. Now, lets investigate further.

```
customers_stay_vis = ggplot(data = customers_stay,
  aes(x = Stay_In_Current_City_Years, y = ..count.., fill =
  Stay_In_Current_City_Years)) +
  geom_bar(stat = 'count') +
  scale_fill_brewer(palette = 15) +
  labs(title = 'Customers Stay in Current City',
    y = 'Count', x = 'Stay in Current City',
    fill = 'Number of Years in Current City')
print(customers_stay_vis)
```



Certainly, a stacked bar chart can provide a clearer visualization of the distribution of customers based on their length of residency within their respective cities, categorized by “*City_Category*”. This chart will aid in uncovering any variations in residency patterns across different city categories. Create this stacked bar chart using the following code:

```

stay_cities = customers_stay %>%
  group_by(City_Category, Stay_In_Current_City_Years) %>%
  tally() %>%
  mutate(Percentage = (n/sum(n))*100)
head(stay_cities)

```

```

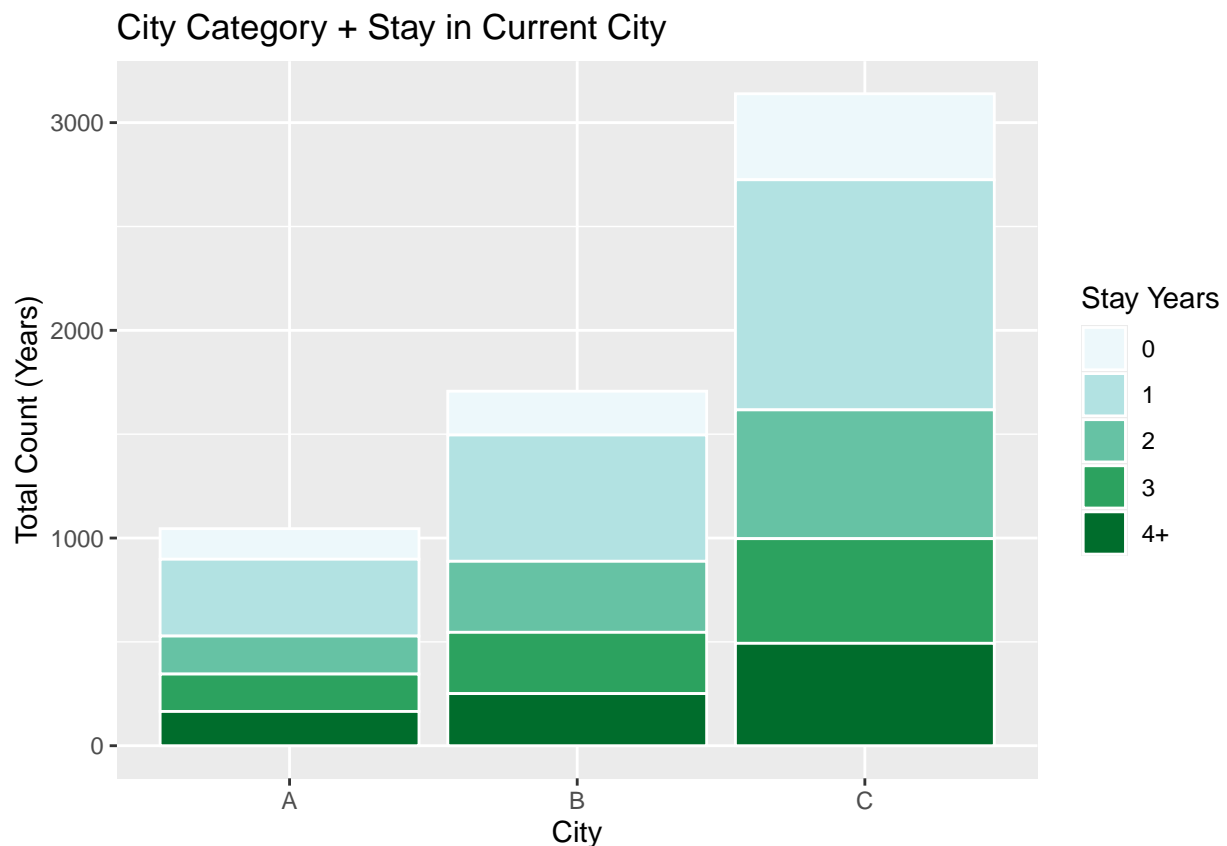
## # A tibble: 6 x 4
## # Groups:   City_Category [2]
##   City_Category Stay_In_Current_City_Years     n Percentage
##   <chr>          <chr>          <int>     <dbl>
## 1 A              0             147      14.1
## 2 A              1             370      35.4
## 3 A              2             183      17.5
## 4 A              3             180      17.2
## 5 A             4+             165      15.8
## 6 B              0             211      12.4

```

```

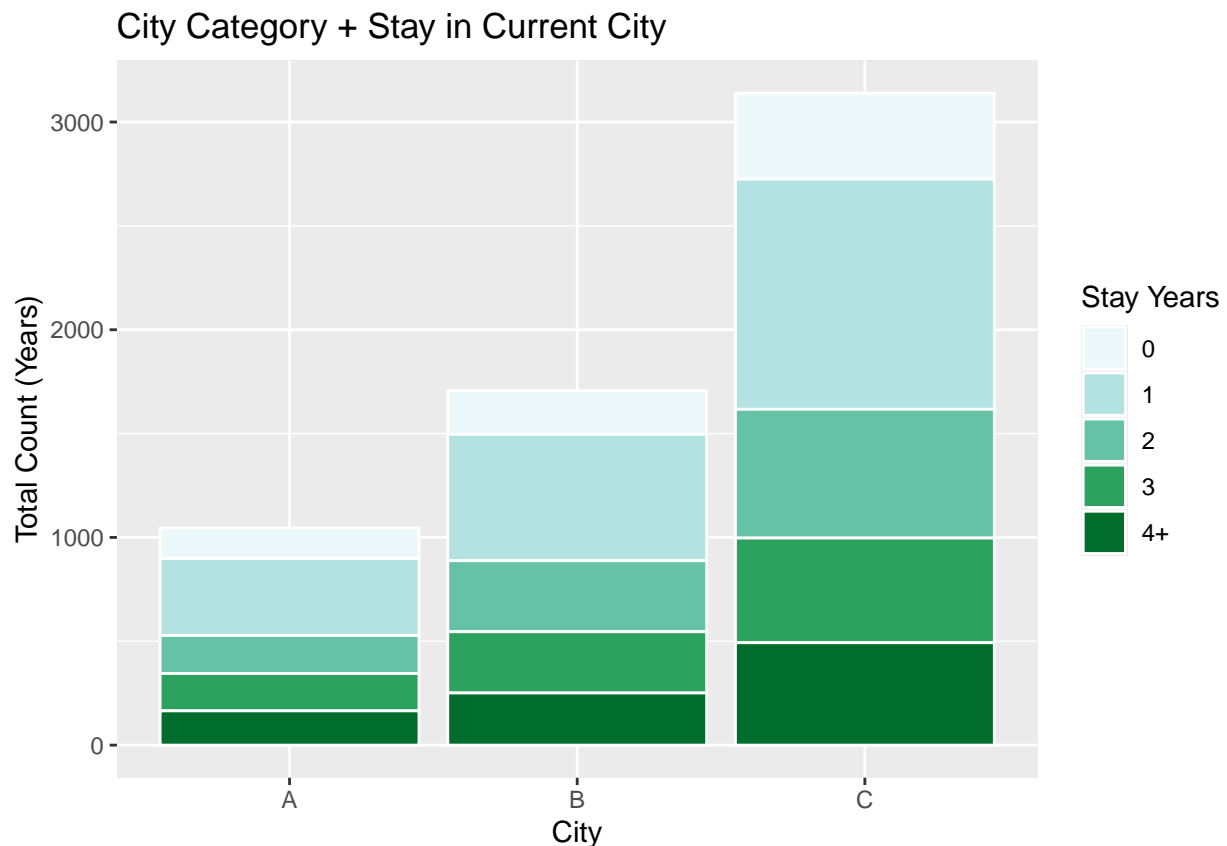
ggplot(data = stay_cities, aes(x = City_Category, y = n, fill =
  Stay_In_Current_City_Years)) +
  geom_bar(stat = "identity", color = 'white') + scale_fill_brewer(palette = 2) +
  labs(title = "City Category + Stay in Current City",
    y = "Total Count (Years)",
    x = "City",
    fill = "Stay Years")

```



This code snippet generates a stacked bar chart that segregates customers' length of residency based on different city categories. This visualization will facilitate the identification of any discernible trends or patterns in customer residency duration across distinct city segments.

```
ggplot(data = stay_cities, aes(x = City_Category, y = n,
                              fill = Stay_In_Current_City_Years)) +
  geom_bar(stat = "identity", color = 'white') +
  scale_fill_brewer(palette = 2) +
  labs(title = "City Category + Stay in Current City",
       y = "Total Count (Years)",
       x = "City",
       fill = "Stay Years")
```



Indeed, observation is accurate and insightful. The stacked bar chart effectively illustrates the distribution of the total customer base across various city categories, segmented by the duration of their residency. A consistent trend emerges across all “*City_Category*” segments, where the most prevalent duration of residence for customers is one year.

This commonality in the predominant residency duration across different city categories highlights the potential influence of this temporal aspect on shopping behaviors. The analysis offers valuable insights into how customer behaviors might correlate with the length of time they have resided in their current cities. As a delve into another aspect of analysis, journey of exploration continues to unravel intricate patterns within the dataset.

3.1.2 Purchase

Certainly, let's delve into the analysis regarding store customers and their purchasing behavior. Initial step involves calculating the total purchase amount attributed to each "*User_ID*". This computation can offer insights into the shopping habits and expenditure patterns of individual customers. To initiate this analysis, can utilize the following code:

```
customers_total_purchase_amount = dataset %>%  
  group_by(User_ID) %>%  
  summarise(Purchase_Amount = sum(Purchase))  
  
head(customers_total_purchase_amount)
```

```
## # A tibble: 6 x 2  
##   User_ID Purchase_Amount  
##   <int>         <int>  
## 1 1000001         333481  
## 2 1000002         810353  
## 3 1000003         341635  
## 4 1000004         205987  
## 5 1000005         821001  
## 6 1000006         379450
```

Now that grouped purchases and grouped by User ID, sort and find top spenders.

```
customers_total_purchase_amount = arrange(customers_total_purchase_amount,  
  desc((Purchase_Amount)))  
  
head(customers_total_purchase_amount)
```

```
## # A tibble: 6 x 2  
##   User_ID Purchase_Amount  
##   <int>         <int>  
## 1 1004277        10536783  
## 2 1001680         8699232  
## 3 1002909         7577505  
## 4 1001941         6817493  
## 5 1000424         6573609  
## 6 1004448         6565878
```

Looks like User ID 1004277 is top spender. Lets use `summary()` to see other facets of total customer spending data.

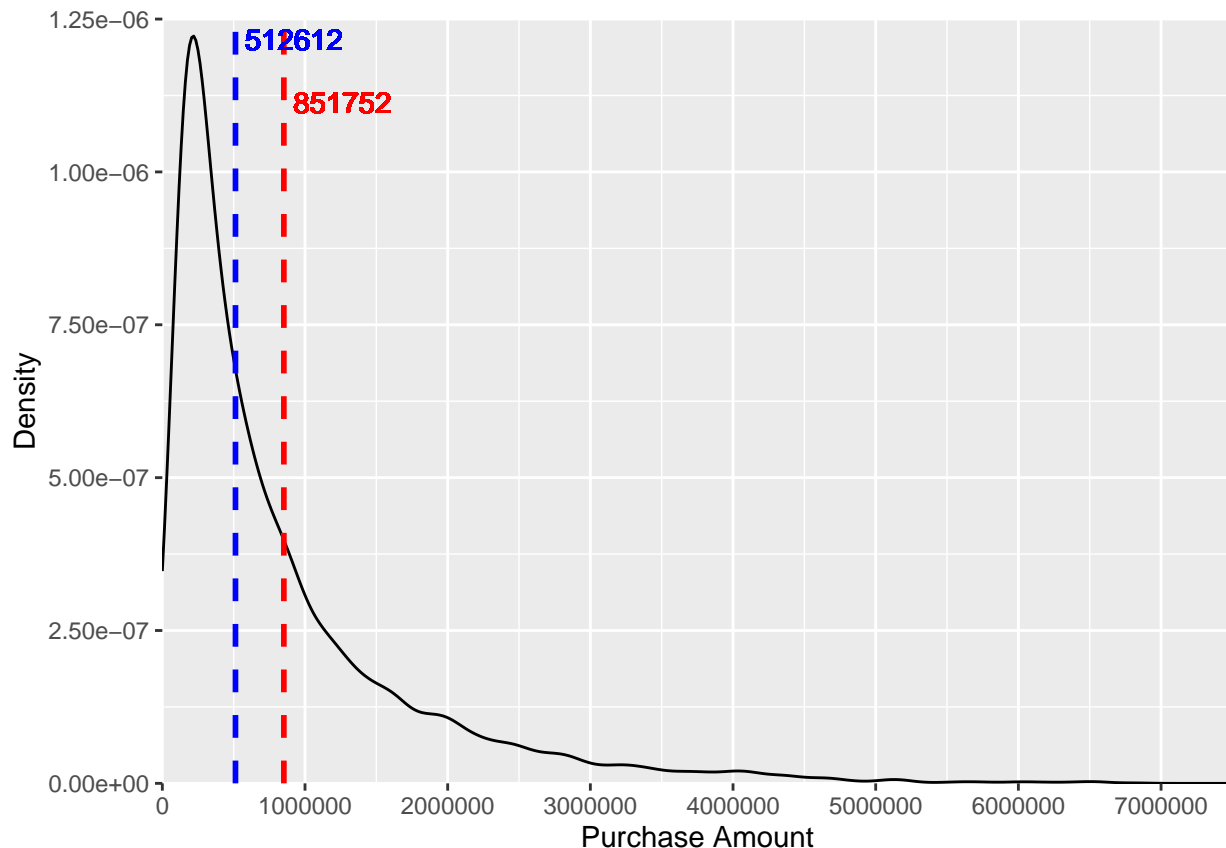
```
summary(customers_total_purchase_amount)
```

```
##   User_ID      Purchase_Amount  
## Min.   :1000001  Min.    :  44108  
## 1st Qu.:1001518  1st Qu.: 234914  
## Median :1003026  Median : 512612  
## Mean   :1003025  Mean    : 851752  
## 3rd Qu.:1004532  3rd Qu.:1099005  
## Max.   :1006040  Max.    :10536783
```

Indeed, these summary statistics provide a comprehensive overview of the distribution of total purchase amounts among customers. It's noteworthy that the average, maximum, minimum, and median values highlight the spread and central tendencies of these purchase amounts. To further delve into the distribution of purchase amounts, a density plot is an excellent choice.

This visualization can help us understand the overall shape and skewness of the data, revealing where the highest concentration of similar purchase amounts lies within the customer base. Create a density plot using the following code:

```
ggplot(customers_total_purchase_amount, aes(Purchase_Amount)) +
  geom_density(adjust = 1) +
  geom_vline(aes(xintercept=median(Purchase_Amount)),
    color="blue", linetype="dashed", size=1) +
  geom_vline(aes(xintercept=mean(Purchase_Amount)),
    color="red", linetype="dashed", size=1) +
  geom_text(aes(x=mean(Purchase_Amount),
    label=round(mean(Purchase_Amount)), y=1.2e-06), color = 'red',
    angle=360, size=4, vjust=3, hjust=-.1) +
  geom_text(aes(x=median(Purchase_Amount), label=round(median(Purchase_Amount)), y=1.2e-06),
    color = 'blue', angle=360, size=4, vjust=0, hjust=-.1) +
  scale_x_continuous(name="Purchase Amount", limits=c(0, 7500000),
    breaks = seq(0, 7500000, by = 1000000), expand = c(0, 0)) +
  scale_y_continuous(name="Density", limits=c(0, .00000125),
    labels = scientific, expand = c(0, 0))
```



3.1.3 Interpretation of the density plot

Interpretation of the density plot is accurate. The observed right (positive) skewness and the extended tail signify that a substantial number of purchase amounts lie higher than the mean. Additionally, the distribution doesn't align with a standard normal distribution.

The peak density around the 250,000 mark indicates that the highest concentration of purchases occurs within this range. This insight corroborates the notion that a significant proportion of customers are making purchases around this amount. Understanding the distribution of purchase amounts is crucial for retailers in tailoring their marketing strategies, discounts, and promotions to effectively engage with their customer base.

This detailed analysis of purchase amounts provides valuable insights into customer spending behavior, further enhancing understanding of the dataset's dynamics. As continue to explore various facets of the data, journey of analysis unfolds, potentially revealing more intricate patterns and trends.

3.1.4 Marital Status

Lets now examine the marital status of store customers.

```
dataset_maritalStatus = dataset %>%
  select(User_ID, Marital_Status) %>%
  group_by(User_ID) %>%
  distinct()

head(dataset_maritalStatus)
```

```
## # A tibble: 6 x 2
## # Groups:   User_ID [6]
##   User_ID Marital_Status
##   <int>      <int>
## 1 1000001          0
## 2 1000002          0
## 3 1000003          0
## 4 1000004          1
## 5 1000005          1
## 6 1000006          0
```

Note, need to quickly change Marital_Status from a numeric variable to a categorical type.

```
dataset_maritalStatus$Marital_Status = as.character(dataset_maritalStatus$Marital_Status)
typeof(dataset_maritalStatus$Marital_Status)
```

```
## [1] "character"
```

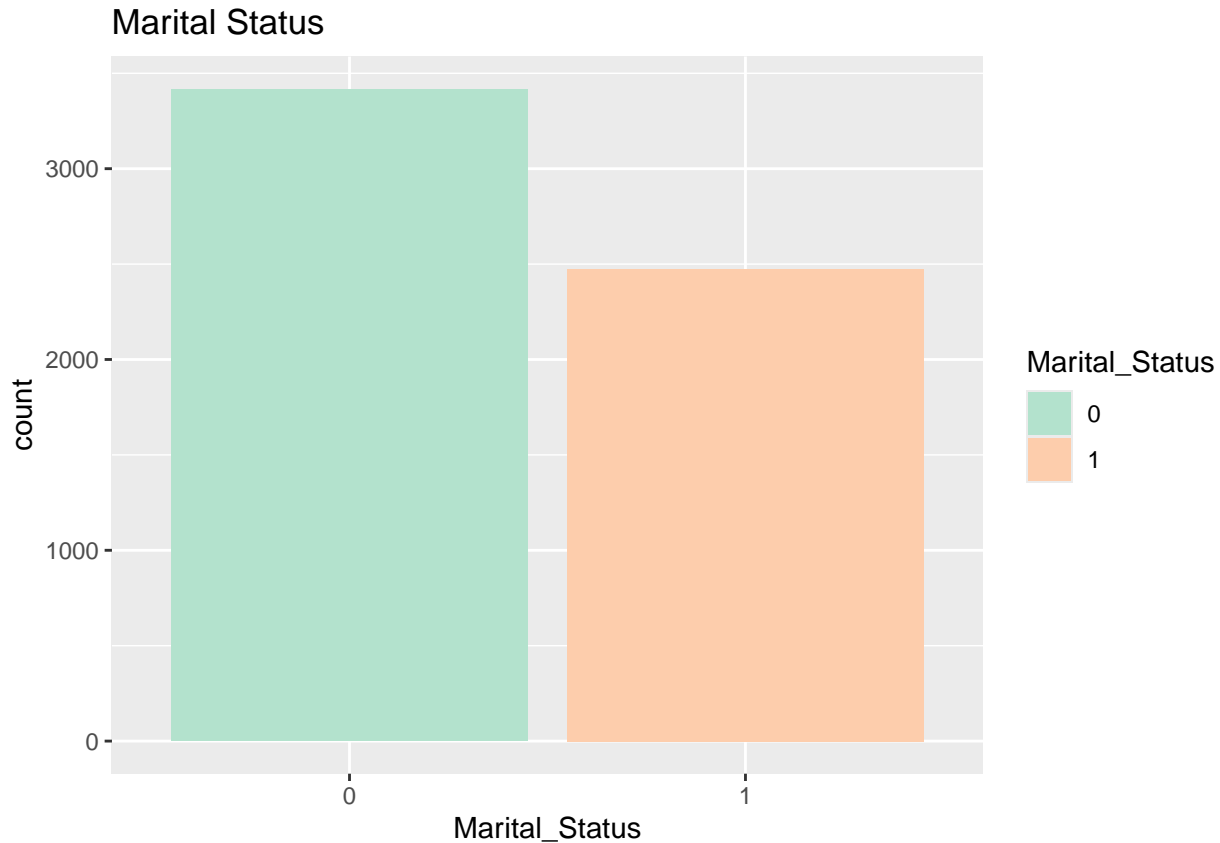
Approach of assuming that 1 represents “*married*” and 0 represents “*single*” for the marital status variable is a reasonable approach given the absence of clear guidance in the dataset's variable descriptions. While it's always ideal to verify such information with the data provider, making educated assumptions based on context and conventional interpretations can help proceed with analysis.

This assumption aligns with common conventions and allows to continue exploring the relationships between marital status and other variables within the dataset. However, do keep in mind that assumptions like these should be documented and clearly communicated when presenting findings to ensure transparency in analysis.

```

marital_vis = ggplot(data = dataset_maritalStatus) +
  geom_bar(mapping = aes(x = Marital_Status, y = ..count..,
                        fill = Marital_Status)) +
  labs(title = 'Marital Status') +
  scale_fill_brewer(palette = 'Pastel2')
print(marital_vis)

```



Indeed, observation aligns with the dataset's pattern, revealing that a significant portion of shoppers appear to be single or unmarried. This insight is valuable in understanding the demographic composition of the customer base.

Extending this analysis, exploring the distribution of “*Marital_Status*” within different “*City_Category*” segments can provide further insights into how marital status varies across different geographical areas. This investigation can shed light on potential regional patterns in shopping behaviors. Conduct this analysis by employing the following code:

```

dataset_maritalStatus = dataset_maritalStatus %>%
  full_join(customers_stay, by = 'User_ID')
head(dataset_maritalStatus)

```

```

## # A tibble: 6 x 4
## # Groups:   User_ID [6]
##   User_ID Marital_Status City_Category Stay_In_Current_City_Years
##   <int> <chr>          <chr>          <chr>
## 1 1000001 0                A                2
## 2 1000002 0                C               4+

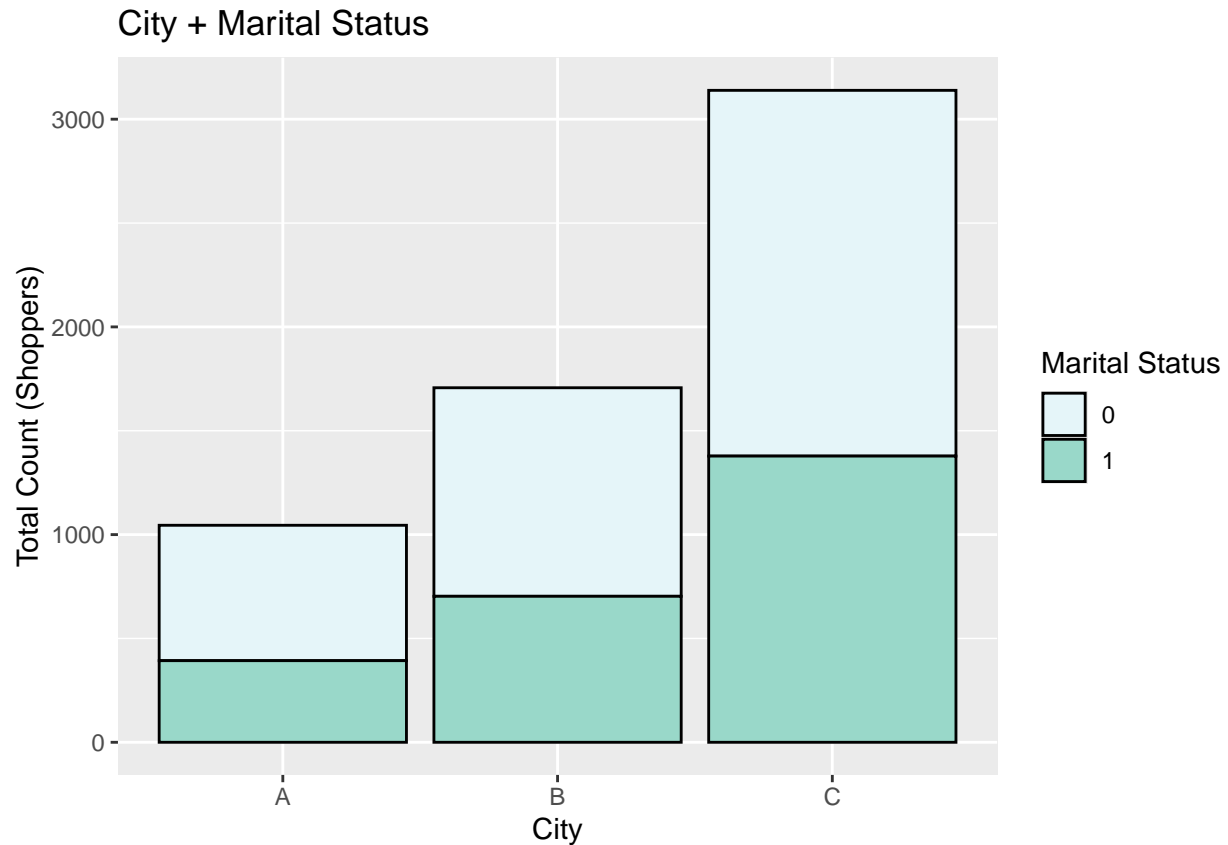
```

```
## 3 1000003 0      A      3
## 4 1000004 1      B      2
## 5 1000005 1      A      1
## 6 1000006 0      A      1
```

```
maritalStatus_cities = dataset_maritalStatus %>%
  group_by(City_Category, Marital_Status) %>%
  tally()
head(maritalStatus_cities)
```

```
## # A tibble: 6 x 3
## # Groups:   City_Category [3]
##   City_Category Marital_Status     n
##   <chr>         <chr>         <int>
## 1 A             0             652
## 2 A             1             393
## 3 B             0            1004
## 4 B             1             703
## 5 C             0            1761
## 6 C             1            1378
```

```
ggplot(data = maritalStatus_cities, aes(x = City_Category, y = n,
                                         fill = Marital_Status)) +
  geom_bar(stat = "identity", color = 'black') +
  scale_fill_brewer(palette = 2) +
  labs(title = "City + Marital Status",
       y = "Total Count (Shoppers)",
       x = "City",
       fill = "Marital Status")
```



Observation about the distribution of single shoppers across different city categories is insightful and provides an initial understanding of how marital status may vary geographically.

Moving forward, can delve into the distribution of “*Stay_in_Current_City*” within each “*City_Category*”. This investigation aims to uncover patterns in the duration of customers’ current city residence across different city segments. Conduct this analysis using the following code:

```
Users_Age = dataset %>%
  select(User_ID, Age) %>%
  distinct()
head(Users_Age)
```

```
##   User_ID   Age
## 1 1000001 0-17
## 2 1000002 55+
## 3 1000003 26-35
## 4 1000004 46-50
## 5 1000005 26-35
## 6 1000006 51-55
```

This code generates a table that compiles the count of customers based on the duration of their stay in their current city, segmented by different city categories. Visualizing this data will help understand how customer residence durations differ across various city segments, potentially unveiling trends and insights about customer behaviors and preferences.

```
dataset_maritalStatus = dataset_maritalStatus %>%
  full_join(Users_Age, by = 'User_ID')
head(dataset_maritalStatus)
```

```
## # A tibble: 6 x 5
## # Groups:   User_ID [6]
##   User_ID Marital_Status City_Category Stay_In_Current_City_Years Age
##   <int> <chr>          <chr>          <chr>          <chr>
## 1 1000001 0                A                2            0-17
## 2 1000002 0                C                4+           55+
## 3 1000003 0                A                3            26-35
## 4 1000004 1                B                2            46-50
## 5 1000005 1                A                1            26-35
## 6 1000006 0                A                1            51-55
```

```
City_A = dataset_maritalStatus %>%
  filter(City_Category == 'A')
City_B = dataset_maritalStatus %>%
  filter(City_Category == 'B')
City_C = dataset_maritalStatus %>%
  filter(City_Category == 'C')
head(City_A)
```

```
## # A tibble: 6 x 5
## # Groups:   User_ID [6]
##   User_ID Marital_Status City_Category Stay_In_Current_City_Years Age
##   <int> <chr>          <chr>          <chr>          <chr>
## 1 1000001 0                A                2            0-17
## 2 1000003 0                A                3            26-35
## 3 1000005 1                A                1            26-35
## 4 1000006 0                A                1            51-55
## 5 1000015 0                A                1            26-35
## 6 1000019 0                A                3            0-17
```

```
head(City_B)
```

```
## # A tibble: 6 x 5
## # Groups:   User_ID [6]
##   User_ID Marital_Status City_Category Stay_In_Current_City_Years Age
##   <int> <chr>          <chr>          <chr>          <chr>
## 1 1000004 1                B                2            46-50
## 2 1000007 1                B                1            36-45
## 3 1000010 1                B                4+           36-45
## 4 1000018 0                B                3            18-25
## 5 1000021 0                B                0            18-25
## 6 1000023 1                B                3            36-45
```

```
head(City_C)
```

```
## # A tibble: 6 x 5
## # Groups:   User_ID [6]
```

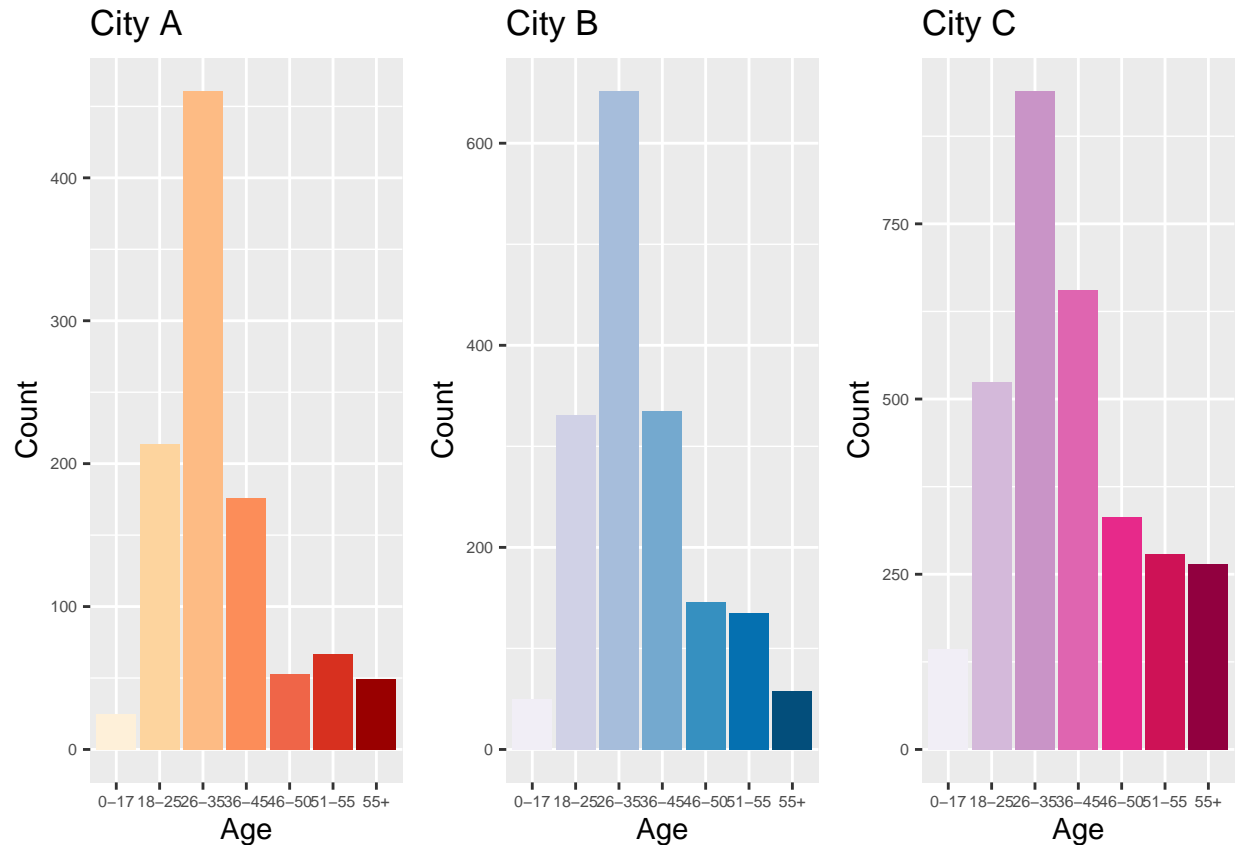
	User_ID	Marital_Status	City_Category	Stay_In_Current_City_Years	Age
	<int>	<chr>	<chr>	<chr>	<chr>
## 1	1000002	0	C	4+	55+
## 2	1000008	1	C	4+	26-35
## 3	1000009	0	C	0	26-35
## 4	1000011	0	C	1	26-35
## 5	1000012	0	C	2	26-35
## 6	1000013	1	C	3	46-50

```

City_A_stay_vis = ggplot(data = City_A, aes(x = Age, y = ..count..,
                                             fill = Age)) +
  geom_bar(stat = 'count') +
  scale_fill_brewer(palette = 8) +
  theme(legend.position="none",
        axis.text = element_text(size = 6)) +
  labs(title = 'City A', y = 'Count', x = 'Age',
        fill = 'Age')
City_B_stay_vis = ggplot(data = City_B, aes(x = Age, y = ..count..,
                                             fill = Age)) +
  geom_bar(stat = 'count') +
  scale_fill_brewer(palette = 9) +
  theme(legend.position="none",
        axis.text = element_text(size = 6)) +
  labs(title = 'City B', y = 'Count', x = 'Age',
        fill = 'Age')
City_C_stay_vis = ggplot(data = City_C, aes(x = Age, y = ..count..,
                                             fill = Age)) +
  geom_bar(stat = 'count') +
  scale_fill_brewer(palette = 11) +
  theme(legend.position="none",
        axis.text = element_text(size = 6)) +
  labs(title = 'City C', y = 'Count', x = 'Age',
        fill = 'Age')

grid.arrange(City_A_stay_vis, City_B_stay_vis, City_C_stay_vis, ncol = 3)

```

Observation regarding the distribution of shoppers over the age of 45 in City A compared to other cities is astute. Indeed, demographic factors such as age distribution can influence various aspects of customer behaviors, including marital status and residency durations.

The interplay between age distribution, marital status, and residency durations can lead to nuanced patterns in each city category. As a mentioned, these factors can collectively shape the resulting levels of marital status within individual cities. This holistic understanding is crucial for retailers and marketers to tailor their strategies and offerings to effectively engage with specific customer segments.

By piecing together various variables and their relationships, effectively unraveling the complexity of customer behaviors within different city categories. As a delve further into the dataset, gaining deeper insights into the dynamics of customer interactions with the store. Analysis showcases the power of data exploration in uncovering hidden trends and patterns.

3.1.5 Top Shoppers

Now, investigate who top shoppers were on Black Friday.

```
top_shoppers = dataset %>%
  count(User_ID, sort = TRUE)

head(top_shoppers)
```

```
##   User_ID    n
## 1 1001680 1025
## 2 1004277  978
```

```
## 3 1001941 898
## 4 1001181 861
## 5 1000889 822
## 6 1003618 766
```

Absolutely, joining the dataset containing information about the top shoppers (“*User_ID*” 1001680 in this case) with the dataset that includes total purchase amounts can provide a comprehensive view of their shopping behavior and expenditure patterns. Perform this joining process using the following code:

```
top_shoppers = top_shoppers %>%
  select(User_ID, n) %>%
  left_join(customers_total_purchase_amount, Purchase_Amount,
            by = 'User_ID')

head(top_shoppers)
```

```
##   User_ID    n Purchase_Amount
## 1 1001680 1025      8699232
## 2 1004277  978     10536783
## 3 1001941  898      6817493
## 4 1001181  861      6387899
## 5 1000889  822      5499812
## 6 1003618  766      5961987
```

In this code snippet, filter the dataset to include information about the top shopper (“*User_ID*” 1001680), selecting relevant columns such as “*User_ID*”, “*Gender*”, “*Age*”, “*City_Category*”, “*Stay_In_Current_City_Years*”, and “*Marital_Status*”. Then perform a left join with the dataset containing total purchase amounts by “*User_ID*”.

The resulting “*top_shopper_combined*” dataset will offer a consolidated view of this top shopper’s demographic information alongside their total purchase amount, providing a comprehensive profile of their shopping behavior. Explore and visualize this combined dataset to gain deeper insights into the shopping patterns of this top shopper.

This analysis can contribute to understanding the behaviors of high-frequency shoppers and potentially inform strategies for customer engagement and retention.

```
top_shoppers = mutate(top_shoppers,
  Average_Purchase_Amount = Purchase_Amount/n)

head(top_shoppers)
```

```
##   User_ID    n Purchase_Amount Average_Purchase_Amount
## 1 1001680 1025      8699232      8487.056
## 2 1004277  978     10536783     10773.807
## 3 1001941  898      6817493      7591.863
## 4 1001181  861      6387899      7419.163
## 5 1000889  822      5499812      6690.769
## 6 1003618  766      5961987      7783.273
```

Indeed, the joined table provides a comprehensive view of the shopping behavior of the top shoppers, highlighting both the *User_ID* with the highest number of total purchases and the “*User_ID*” with the highest total “*Purchase_Amount*”. Continuing analysis, can compute the average “*Purchase_Amount*” for each user using the following code:

```
top_shoppers_averagePurchase = top_shoppers %>%
  arrange(desc(Average_Purchase_Amount))

head(top_shoppers_averagePurchase)
```

```
##   User_ID  n Purchase_Amount Average_Purchase_Amount
## 1 1005069 16      308454      19278.38
## 2 1003902 93     1746284      18777.25
## 3 1005999 18      330227      18345.94
## 4 1001349 23      417743      18162.74
## 5 1000101 65     1138239      17511.37
## 6 1003461 20      350174      17508.70
```

Analysis highlights interesting patterns among the top shoppers. The contrast between “*User_ID*” 1005069 and “*User_ID*” 1003902 is particularly intriguing: while “*User_ID*” 1005069 has the low average purchase amount, “*User_ID*” 1003902 boasts a significantly higher total purchase amount. These differences underscore the significance of considering both average and total purchase amounts when evaluating customer spending behaviors.

High average purchase amounts can indicate a willingness to spend more on individual transactions, while high total purchase amounts reflect a greater cumulative expenditure over multiple transactions. These insights can inform marketing strategies, tailored offers, and customer engagement efforts. Understanding the spending dynamics of individual customers provides valuable guidance for optimizing retail operations and enhancing customer satisfaction. As an analysis continues, painting a detailed picture of the top shoppers’ behaviors, ultimately contributing to a more comprehensive understanding of the dataset’s dynamics.

3.1.6 Occupation

The last thing analyze is the occupation of customers in dataset.

```
customers_Occupation = dataset %>%
  select(User_ID, Occupation) %>%
  group_by(User_ID) %>%
  distinct() %>%
  left_join(customers_total_purchase_amount, Occupation,
    by = 'User_ID')

head(customers_Occupation)
```

```
## # A tibble: 6 x 3
## # Groups:   User_ID [6]
##   User_ID Occupation Purchase_Amount
##   <int>      <int>      <int>
## 1 1000001         10      333481
## 2 1000002         16      810353
## 3 1000003         15      341635
## 4 1000004          7      205987
## 5 1000005         20      821001
## 6 1000006          9      379450
```

Now that dataset necessary, group together the total “*Purchase_Amount*” for each Occupation identifier. Then convert Occupation to a charater data type.

```
totalPurchases_Occupation = customers_Occupation %>%
  group_by(Occupation) %>%
  summarise(Purchase_Amount = sum(Purchase_Amount)) %>%
  arrange(desc(Purchase_Amount))

totalPurchases_Occupation$Occupation =
  as.character(totalPurchases_Occupation$Occupation)
typeof(totalPurchases_Occupation$Occupation)
```

```
## [1] "character"
```

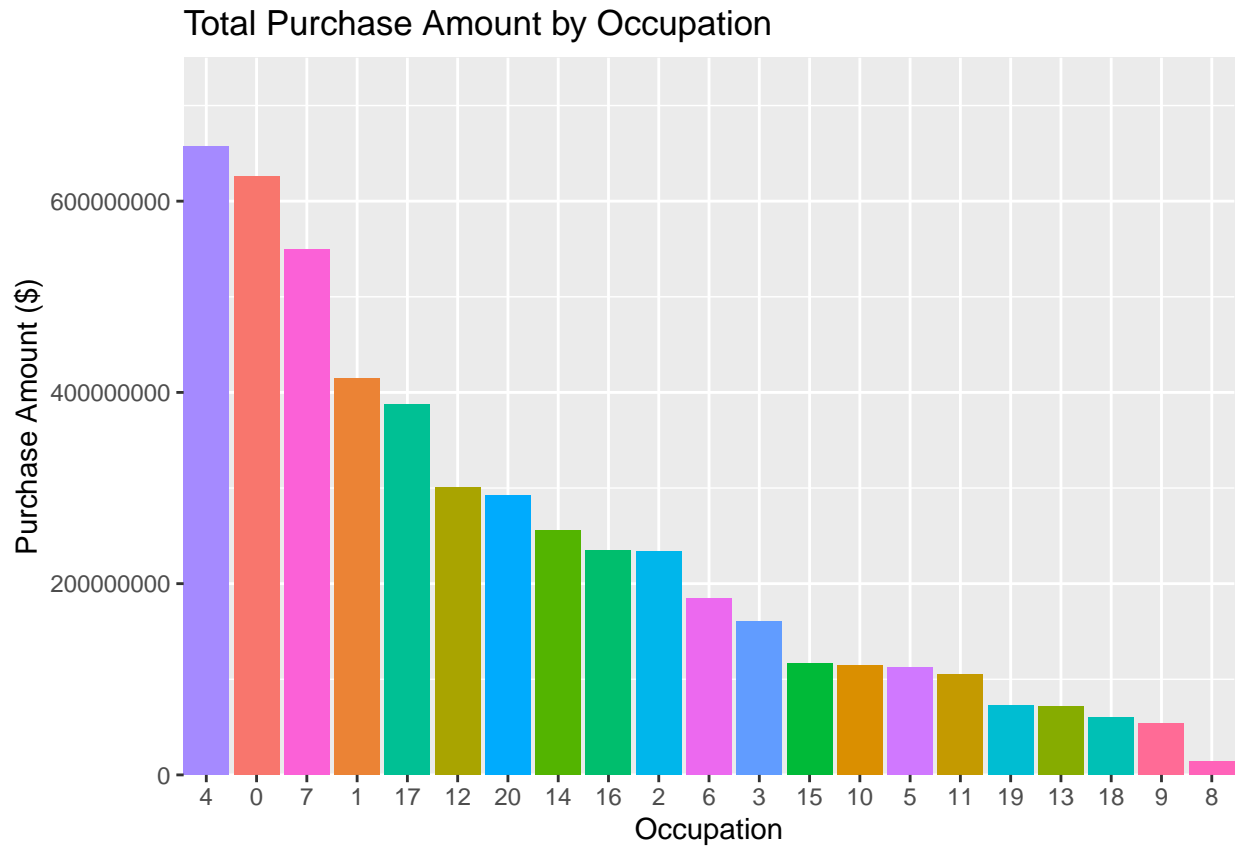
```
head(totalPurchases_Occupation)
```

```
## # A tibble: 6 x 2
##   Occupation Purchase_Amount
##   <chr>          <int>
## 1 4            657530393
## 2 0            625814811
## 3 7            549282744
## 4 1            414552829
## 5 17           387240355
## 6 12           300672105
```

Now, lets plot each occupation and their total Purchase_Amount

```
occupation = ggplot(data = totalPurchases_Occupation) +
  geom_bar(mapping =
    aes(x = reorder(Occupation, -Purchase_Amount),
      y = Purchase_Amount, fill = Occupation),
    stat = 'identity') +
  scale_x_discrete(name="Occupation",
    breaks = seq(0,20, by = 1), expand = c(0,0)) +
  scale_y_continuous(name="Purchase Amount ($)",
    expand = c(0,0), limits = c(0, 750000000)) +
  labs(title = 'Total Purchase Amount by Occupation') +
  theme(legend.position="none")

print(occupation)
```



Looks like customers labeled as Occupation 4 spent the most at store on Black Friday, with customers of Occupation 0 + 7 closely behind. Here, if a key was given, use that information to classify shoppers accordingly.

4 Chapter 4

4.1 Modeling Results and Model Performance

4.1.1 Apriori (Association Rule Learning)

Certainly, the explanation of Association Rule Learning provided is accurate and insightful. Association Rule Learning, epitomized by the Apriori algorithm, holds immense potential for retailers and businesses seeking to uncover hidden patterns in customer purchasing behaviors. By identifying associations between items frequently purchased together, businesses can strategically optimize product placement, cross-selling, and promotional campaigns to enhance sales and customer engagement [4]. The **Apriori algorithm** is a widely used technique in association rule learning, a type of unsupervised ML aimed at discovering interesting relationships or patterns between items in a dataset. It is particularly popular in market basket analysis, where the goal is to find which items are frequently purchased together.

Apriori is used for association rule discovery and finding item relationships, while **linear/logistic regression** is used for prediction or classification. In a broader analysis pipeline, you might use Apriori to discover relationships and use regression models to predict outcomes based on those relationships.

The Apriori algorithm was chosen for its ability to identify associations and frequent itemsets within transactional data. This is particularly suited for analyzing retail datasets like Black Friday, where understanding product relationships and consumer purchasing patterns can provide actionable insights.

1. **Relevance to Retail Analysis:** The Apriori algorithm excels in discovering frequent combinations of items purchased together, which is vital for optimizing product placement, cross-selling, and promotional strategies. Its use in this context helps retailers understand how demographic factors influence purchasing behavior and product preferences.
2. **Scalability and Interpretability:** Apriori is computationally efficient for datasets with structured transactional data. The rules generated are straightforward, making them easy to interpret and apply in retail decision-making processes.
3. **Enhancement of Insights:** Using the Apriori algorithm complements exploratory data analysis by providing deeper insights into relationships between products and consumer behavior.

The focus on demographic variables such as Gender, Age, and City Category was driven by their direct relevance to retail strategies:

1. **Gender:** Understanding gender-based purchasing behaviors informs targeted marketing and inventory decisions.
2. **Age Groups:** Different age groups exhibit distinct spending patterns, which are essential for segmentation and personalized offers.
3. **City Category:** Analyzing city categories highlights regional preferences and helps in resource allocation for promotions and stock.

Apriori algorithm, in particular, strives to unearth the most probable associations among items, enabling the generation of rules like “*People who bought item A also bought item B.*” This algorithm’s applications extend beyond retail to various domains, including recommendation systems, market basket analysis, and more [5][6].

As an embark on implementing the Apriori algorithm using the `arules` package, ensure that have imported the required libraries to facilitate the analysis. If haven’t imported the libraries yet, can use the following code:

```

if (!require(arules)) {
  install.packages("arules", repos = "http://cran.us.r-project.org")
}
if (!require(arulesViz)) {
  install.packages("arulesViz", repos = "http://cran.us.r-project.org")
}
if (!require(tidyverse)) {
  install.packages("tidyverse", repos = "http://cran.us.r-project.org")
}

library(arules)
library(arulesViz)
library(tidyverse)

```

With these libraries in place, well-equipped to proceed with Association Rule Learning analysis. This endeavor will yield valuable insights into purchase associations, aiding retailers in optimizing their strategies and enhancing customer experiences.

If need assistance with the implementation or interpretation of the Apriori algorithm, to reach out for guidance. The arules package was developed specifically to deal with Association Rule and Frequent Itemset mining. In order to begin analysis, retrieve the necessary data from the original dataset and then apply the correct formatting.

```

# Data Preprocessing
# Getting the dataset into the correct format
customers_products = dataset %>%
  select(User_ID, Product_ID) %>%
  # Selecting the columns we will need
  group_by(User_ID) %>%
  # Grouping by "User_ID"
  arrange(User_ID) %>%
  # Arranging by "User_ID"
  mutate(id = row_number()) %>%
  # Defining a key column for each "Product_ID" and its corresponding
  # "User_ID" (Must do this for spread() to work properly)
  spread(User_ID, Product_ID) %>%
  # Converting our dataset from tall to wide format, and grouping
  # "Product_IDs" to their corresponding "User_ID"
  t()
# Transposing the dataset from columns of "User_ID" to rows of "User_ID"

# Now we can remove the Id row we created earlier for spread() to work correctly.
customers_products = customers_products[-1,]

```

Explanation of the process to prepare the data for the Apriori algorithm is accurate. The Apriori algorithm indeed requires a binary format, where products are represented as columns, and a value of 1 indicates that a customer purchased that product, while a value of 0 indicates no purchase. This transformation from the original dataset to a sparse matrix format is a necessary step to facilitate the Apriori algorithm's analysis.

Here's how can perform this transformation using the arules library:

1. Save “customers_products” table as a CSV file.

2. Use the `read.transactions()` function to read the CSV file and convert it into the required sparse matrix format.

Here's an example code snippet to achieve this:

```
write.csv(customers_products, file = 'customers_products.csv')

customersProducts = read.transactions('customers_products.csv', sep = ',', rm.duplicates = TRUE)
```

```
## distribution of transactions with duplicates:
## items
## 46 126 163 202 258 272 285 307 310 316 319 327 330 334 340 344
## 1 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1
## 345 348 354 357 373 393 402 408 419 437 441 449 450 452 454 456
## 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## 459 465 466 467 475 476 477 481 487 491 495 498 507 523 524 526
## 1 1 2 2 1 1 1 1 2 2 3 2 1 1 2 1
## 527 528 530 531 532 533 535 537 538 539 540 545 546 548 549 553
## 2 1 1 2 1 1 1 1 2 3 1 1 1 3 1 1
## 554 555 556 558 563 566 567 570 572 574 575 577 578 580 583 584
## 2 1 1 2 1 3 1 3 2 4 1 2 3 2 1 1
## 586 588 589 590 591 592 593 594 595 597 598 601 602 604 607 608
## 2 3 5 1 1 1 1 1 3 2 1 1 1 1 2 1
## 610 612 613 614 615 616 617 618 619 620 623 625 632 633 634 635
## 1 2 1 2 1 1 2 1 3 2 1 1 6 1 5 2
## 638 640 641 642 643 644 645 646 647 648 653 654 657 658 659 661
## 2 2 1 2 1 2 3 1 4 1 1 3 2 1 1 2
## 662 663 664 665 666 667 668 669 670 671 672 674 676 677 678 679
## 1 3 1 1 2 1 2 4 2 1 3 1 1 2 3 3
## 681 682 683 685 686 687 688 689 690 691 692 694 695 697 698 699
## 2 2 4 4 5 2 2 1 1 1 1 2 1 1 1 1
## 700 702 703 704 705 706 707 708 709 710 712 713 714 715 716 717
## 2 1 3 1 1 2 2 3 2 2 4 5 2 2 1 1
## 718 719 720 721 722 723 724 725 726 727 728 729 730 732 733 734
## 2 3 3 5 2 1 1 2 5 2 1 3 3 2 1 5
## 735 736 737 738 739 740 741 742 743 744 745 747 748 749 750 751
## 6 2 4 6 3 4 1 6 7 4 6 1 1 5 5 3
## 752 753 754 755 756 757 758 759 760 761 763 764 765 766 767 768
## 2 3 4 6 6 2 6 2 1 5 3 4 2 3 2 5
## 769 770 771 772 773 774 775 776 777 778 779 780 781 782 783 784
## 2 2 3 1 3 4 2 2 3 3 2 4 7 3 4 5
## 785 786 787 788 789 790 791 792 793 794 795 796 797 798 799 800
## 5 3 3 6 5 5 2 3 5 3 8 5 5 9 3 4
## 801 802 803 804 805 806 807 808 809 810 811 812 813 814 815 816
## 4 7 4 3 4 5 7 5 4 5 3 2 6 6 3 11
## 817 818 819 820 821 822 823 824 825 826 827 828 829 830 831 832
## 5 10 6 6 4 7 7 2 5 4 7 5 5 4 5 4
## 833 834 835 836 837 838 839 840 841 842 843 844 845 846 847 848
## 3 5 4 11 5 5 4 9 7 6 4 7 9 11 4 6
## 849 850 851 852 853 854 855 856 857 858 859 860 861 862 863 864
## 10 6 10 7 12 16 11 8 7 4 12 9 11 11 9 6
## 865 866 867 868 869 870 871 872 873 874 875 876 877 878 879 880
## 11 10 7 6 5 12 6 7 8 11 9 9 8 7 5 4
```



```
## 881 882 883 884 885 886 887 888 889 890 891 892 893 894 895 896
## 15 13 12 8 4 6 12 15 13 10 11 13 6 21 7 14
## 897 898 899 900 901 902 903 904 905 906 907 908 909 910 911 912
## 9 7 11 18 5 14 10 9 19 15 10 17 18 23 8 19
## 913 914 915 916 917 918 919 920 921 922 923 924 925 926 927 928
## 15 12 18 21 17 12 11 13 13 12 20 20 16 13 15 17
## 929 930 931 932 933 934 935 936 937 938 939 940 941 942 943 944
## 27 22 20 28 18 14 20 20 20 14 22 30 23 23 21 20
## 945 946 947 948 949 950 951 952 953 954 955 956 957 958 959 960
## 25 19 30 31 30 24 27 25 40 30 31 16 29 30 32 48
## 961 962 963 964 965 966 967 968 969 970 971 972 973 974 975 976
## 27 27 24 30 26 35 43 30 51 49 40 41 36 32 36 38
## 977 978 979 980 981 982 983 984 985 986 987 988 989 990 991 992
## 43 41 42 37 49 44 51 57 55 40 53 56 63 39 58 50
## 993 994 995 996 997 998 999 1000 1001 1002 1003 1004 1005 1006 1007 1008
## 58 77 74 72 72 84 74 66 77 85 93 79 94 118 122 104
## 1009 1010 1011 1012 1013 1014 1015 1016 1017 1018 1019
## 121 113 120 78 77 55 37 20 7 5 1
```

```
# remove duplicates with rm.duplicates
```

Before implement the Apriori algorithm to problem, lets take a look at newly created sparse matrix.

```
summary(customersProducts)
```

```
## transactions as itemMatrix in sparse format with
## 5892 rows (elements/itemsets/transactions) and
## 10539 columns (items) and a density of 0.008768598
##
## most frequent items:
## P00265242 P00110742 P00025442 P00112142 P00057642 (Other)
## 1858 1591 1586 1539 1430 536489
##
## element (itemset/transaction) length distribution:
## sizes
## 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21
## 1 5 7 20 37 55 77 78 120 113 121 104 122 118 94 79
## 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37
## 93 85 77 66 74 84 72 72 74 77 58 50 58 39 63 56
## 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53
## 53 40 55 57 51 44 49 37 42 41 43 38 36 32 36 41
## 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69
## 40 49 51 30 43 35 26 30 24 27 27 48 32 30 29 16
## 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85
## 31 30 40 25 27 24 30 31 30 19 25 20 21 23 23 30
## 86 87 88 89 90 91 92 93 94 95 96 97 98 99 100 101
## 22 14 20 20 20 14 18 28 20 22 27 17 15 13 16 20
## 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117
## 20 12 13 13 11 12 17 21 18 12 15 19 8 23 18 17
## 118 119 120 121 122 123 124 125 126 127 128 129 130 131 132 133
## 10 15 19 9 10 14 5 18 11 7 9 14 7 21 6 13
## 134 135 136 137 138 139 140 141 142 143 144 145 146 147 148 149
## 11 10 13 15 12 6 4 8 12 13 15 4 5 7 8 9
```

```

## 150 151 152 153 154 155 156 157 158 159 160 161 162 163 164 165
## 9 11 8 7 6 12 5 6 7 10 11 6 9 11 11 9
## 166 167 168 169 170 171 172 173 174 175 176 177 178 179 180 181
## 12 4 7 8 11 16 12 7 10 6 10 6 4 11 9 7
## 182 183 184 185 186 187 188 189 190 191 192 193 194 195 196 197
## 4 6 7 9 4 5 5 11 4 5 3 4 5 4 5 5
## 198 199 200 201 202 203 204 205 206 207 208 209 210 211 212 213
## 7 4 5 2 7 7 4 6 6 10 5 11 3 6 6 2
## 214 215 216 217 218 219 220 221 222 223 224 225 226 227 228 229
## 3 5 4 5 7 5 4 3 4 7 4 4 3 9 5 5
## 230 231 232 233 234 235 236 237 238 239 240 241 242 243 244 245
## 8 3 5 3 2 5 5 6 3 3 5 5 4 3 7 4
## 246 247 248 249 250 251 252 253 254 255 256 257 258 259 260 261
## 2 3 3 2 2 4 3 1 3 2 2 5 2 3 2 4
## 262 264 265 266 267 268 269 270 271 272 273 274 275 276 277 278
## 3 5 1 2 6 2 6 6 4 3 2 3 5 5 1 1
## 280 281 282 283 284 285 286 287 288 289 290 291 292 293 295 296
## 6 4 7 6 1 4 3 6 4 2 6 5 1 2 3 3
## 297 298 299 300 301 302 303 304 305 306 307 308 309 310 311 312
## 1 2 5 2 1 1 2 5 3 3 2 1 1 2 2 5
## 313 315 316 317 318 319 320 321 322 323 325 326 327 328 330 331
## 4 2 2 3 2 2 1 1 3 1 2 1 1 1 1 2
## 333 334 335 336 337 338 339 340 342 343 344 346 347 348 349 351
## 1 1 1 1 2 2 5 4 4 2 2 3 3 2 1 1
## 353 354 355 356 357 358 359 360 361 362 363 364 366 367 368 371
## 3 1 2 4 2 1 2 1 1 3 1 2 1 1 2 3
## 372 377 378 379 380 381 382 383 384 385 387 390 391 392 393 400
## 1 1 4 1 3 2 1 2 1 2 2 2 5 1 6 1
## 402 405 406 407 408 409 410 411 412 413 415 417 418 421 423 424
## 1 2 3 1 2 1 1 2 1 2 1 1 2 1 1 1
## 427 428 430 431 432 433 434 435 436 437 439 441 442 445 447 448
## 1 2 3 1 1 1 1 1 5 3 2 1 1 2 3 2
## 450 451 453 455 458 459 462 467 469 470 471 472 476 477 479 480
## 1 4 2 3 1 3 1 2 1 1 2 1 1 3 1 1
## 485 486 487 488 490 492 493 494 495 497 498 499 501 502 518 527
## 1 3 2 1 1 1 1 2 1 1 2 1 2 1 1 2
## 530 534 538 544 548 549 550 558 559 560 566 569 571 573 575 576
## 3 2 2 1 1 1 1 2 2 1 1 1 1 1 1 1
## 584 588 606 617 623 632 652 668 671 677 680 681 685 691 695 698
## 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2
## 706 709 715 718 740 753 767 823 862 899 979 1025 1026
## 1 1 1 1 1 1 1 1 1 1 1 1 1
##
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 6.00 26.00 54.00 92.41 115.00 1026.00
##
## includes extended item information - examples:
## labels
## 1 1000001
## 2 1000002
## 3 1000003

```

Analysis and interpretation of the sparse matrix characteristics are accurate. The summary of the sparse matrix provides essential insights into the data's density, showcasing the proportion of non-zero (1) values

compared to zero (0) values.

This density value, which is approximately 0.009, indicates that around 0.9% of the entries in the sparse matrix are non-zero, implying that 99.1% of the matrix entries are zero. Additionally, the frequent items identified in the summary of the sparse matrix align with the insights uncovered during Exploratory Data Analysis.

This congruence underscores the consistency and reliability of findings across different stages of analysis. Extract the most frequent items from the sparse matrix using the following code:

```
summary(customersProducts)
```

```
## transactions as itemMatrix in sparse format with
## 5892 rows (elements/itemsets/transactions) and
## 10539 columns (items) and a density of 0.008768598
##
## most frequent items:
## P00265242 P00110742 P00025442 P00112142 P00057642 (Other)
##      1858      1591      1586      1539      1430      536489
##
## element (itemset/transaction) length distribution:
## sizes
##      6      7      8      9     10     11     12     13     14     15     16     17     18     19     20     21
##      1      5      7     20     37     55     77     78    120    113    121    104    122    118     94     79
##     22     23     24     25     26     27     28     29     30     31     32     33     34     35     36     37
##     93     85     77     66     74     84     72     72     74     77     58     50     58     39     63     56
##     38     39     40     41     42     43     44     45     46     47     48     49     50     51     52     53
##     53     40     55     57     51     44     49     37     42     41     43     38     36     32     36     41
##     54     55     56     57     58     59     60     61     62     63     64     65     66     67     68     69
##     40     49     51     30     43     35     26     30     24     27     27     48     32     30     29     16
##     70     71     72     73     74     75     76     77     78     79     80     81     82     83     84     85
##     31     30     40     25     27     24     30     31     30     19     25     20     21     23     23     30
##     86     87     88     89     90     91     92     93     94     95     96     97     98     99    100    101
##     22     14     20     20     20     14     18     28     20     22     27     17     15     13     16     20
##    102    103    104    105    106    107    108    109    110    111    112    113    114    115    116    117
##     20     12     13     13     11     12     17     21     18     12     15     19     8      23     18     17
##    118    119    120    121    122    123    124    125    126    127    128    129    130    131    132    133
##     10     15     19     9      10     14     5      18     11     7      9      14     7      21     6      13
##    134    135    136    137    138    139    140    141    142    143    144    145    146    147    148    149
##     11     10     13     15     12     6       4       8     12     13     15     4       5       7       8       9
##    150    151    152    153    154    155    156    157    158    159    160    161    162    163    164    165
##     9      11     8       7       6      12     5       6       7     10     11     6       9     11     11     9
##    166    167    168    169    170    171    172    173    174    175    176    177    178    179    180    181
##     12     4       7       8     11     16     12     7     10     6     10     6       4     11     9       7
##    182    183    184    185    186    187    188    189    190    191    192    193    194    195    196    197
##     4       6       7       9       4       5       5     11     4       5     3       4       5       4       5       5
##    198    199    200    201    202    203    204    205    206    207    208    209    210    211    212    213
##     7       4       5       2       7       7       4       6       6     10     5     11     3       6       6       2
##    214    215    216    217    218    219    220    221    222    223    224    225    226    227    228    229
##     3       5       4       5       7       5       4       3       4       7       4       4       3       9       5       5
##    230    231    232    233    234    235    236    237    238    239    240    241    242    243    244    245
##     8       3       5       3       2       5       5       6       3       3       5       5       4       3       7       4
##    246    247    248    249    250    251    252    253    254    255    256    257    258    259    260    261
##     2       3       3       2       2       4       3       1       3       2       2       5       2       3       2       4
##    262    264    265    266    267    268    269    270    271    272    273    274    275    276    277    278
```

```

##      3      5      1      2      6      2      6      6      4      3      2      3      5      5      1      1
## 280 281 282 283 284 285 286 287 288 289 290 291 292 293 295 296
##      6      4      7      6      1      4      3      6      4      2      6      5      1      2      3      3
## 297 298 299 300 301 302 303 304 305 306 307 308 309 310 311 312
##      1      2      5      2      1      1      2      5      3      3      2      1      1      2      2      5
## 313 315 316 317 318 319 320 321 322 323 325 326 327 328 330 331
##      4      2      2      3      2      2      1      1      3      1      2      1      1      1      1      2
## 333 334 335 336 337 338 339 340 342 343 344 346 347 348 349 351
##      1      1      1      1      2      2      5      4      4      2      2      3      3      2      1      1
## 353 354 355 356 357 358 359 360 361 362 363 364 366 367 368 371
##      3      1      2      4      2      1      2      1      1      3      1      2      1      1      2      3
## 372 377 378 379 380 381 382 383 384 385 387 390 391 392 393 400
##      1      1      4      1      3      2      1      2      1      2      2      2      5      1      6      1
## 402 405 406 407 408 409 410 411 412 413 415 417 418 421 423 424
##      1      2      3      1      2      1      1      2      1      2      1      1      2      1      1      1
## 427 428 430 431 432 433 434 435 436 437 439 441 442 445 447 448
##      1      2      3      1      1      1      1      1      5      3      2      1      1      2      3      2
## 450 451 453 455 458 459 462 467 469 470 471 472 476 477 479 480
##      1      4      2      3      1      3      1      2      1      1      2      1      1      3      1      1
## 485 486 487 488 490 492 493 494 495 497 498 499 501 502 518 527
##      1      3      2      1      1      1      1      2      1      1      2      1      2      1      1      2
## 530 534 538 544 548 549 550 558 559 560 566 569 571 573 575 576
##      3      2      2      1      1      1      1      2      2      1      1      1      1      1      1      1
## 584 588 606 617 623 632 652 668 671 677 680 681 685 691 695 698
##      1      1      1      1      1      1      1      1      1      1      1      1      1      1      1      2
## 706 709 715 718 740 753 767 823 862 899 979 1025 1026
##      1      1      1      1      1      1      1      1      1      1      1      1      1      1
##
##      Min. 1st Qu.  Median      Mean 3rd Qu.      Max.
##      6.00  26.00   54.00   92.41  115.00  1026.00
##
## includes extended item information - examples:
##      labels
## 1 1000001
## 2 1000002
## 3 1000003

```

The `itemFrequency()` function calculates the frequency of each item in the transactions data, and `head()` is used to display the top 10 most frequent items. Comparing these results to earlier analyses helps validate the accuracy of insights.

By cross-referencing and confirming findings through multiple analyses, ensuring the robustness of conclusions and contributing to a more comprehensive understanding of customer purchase behaviors. To continue analysis, and if any further questions or need assistance with interpreting the results of the Apriori algorithm, don't hesitate to ask.

1. P00265242 = 1858
2. P00110742 = 1591
3. P00025442 = 1586
4. P00112142 = 1539
5. P00057642 = 1430
6. (Other) = 536489

Now lets compare it to what discovered earlier. *“Looks like top 5 best sellers are (by product ID)”*

1. P00265242 = 1858
2. P00110742 = 1591
3. P00025442 = 1586
4. P00112142 = 1539
5. P00057642 = 1430

```
summary(customersProducts)
```

```
## transactions as itemMatrix in sparse format with
## 5892 rows (elements/itemsets/transactions) and
## 10539 columns (items) and a density of 0.008768598
##
## most frequent items:
## P00265242 P00110742 P00025442 P00112142 P00057642 (Other)
##      1858      1591      1586      1539      1430    536489
##
## element (itemset/transaction) length distribution:
## sizes
##      6      7      8      9     10     11     12     13     14     15     16     17     18     19     20     21
##      1      5      7     20     37     55     77     78    120    113    121    104    122    118     94     79
##     22     23     24     25     26     27     28     29     30     31     32     33     34     35     36     37
##     93     85     77     66     74     84     72     72     74     77     58     50     58     39     63     56
##     38     39     40     41     42     43     44     45     46     47     48     49     50     51     52     53
##     53     40     55     57     51     44     49     37     42     41     43     38     36     32     36     41
##     54     55     56     57     58     59     60     61     62     63     64     65     66     67     68     69
##     40     49     51     30     43     35     26     30     24     27     27     48     32     30     29     16
##     70     71     72     73     74     75     76     77     78     79     80     81     82     83     84     85
##     31     30     40     25     27     24     30     31     30     19     25     20     21     23     23     30
##     86     87     88     89     90     91     92     93     94     95     96     97     98     99    100    101
##     22     14     20     20     20     14     18     28     20     22     27     17     15     13     16     20
##    102    103    104    105    106    107    108    109    110    111    112    113    114    115    116    117
##     20     12     13     13     11     12     17     21     18     12     15     19     8      23     18     17
##    118    119    120    121    122    123    124    125    126    127    128    129    130    131    132    133
##     10     15     19     9      10     14     5      18     11     7      9      14     7      21     6      13
##    134    135    136    137    138    139    140    141    142    143    144    145    146    147    148    149
##     11     10     13     15     12     6      4      8     12     13     15     4      5      7      8      9
##    150    151    152    153    154    155    156    157    158    159    160    161    162    163    164    165
##     9      11     8      7      6      12     5      6      7     10     11     6      9     11     11     9
##    166    167    168    169    170    171    172    173    174    175    176    177    178    179    180    181
##     12     4      7      8     11     16     12     7     10     6     10     6      4     11     9      7
##    182    183    184    185    186    187    188    189    190    191    192    193    194    195    196    197
##     4      6      7      9      4      5      5     11     4      5      3      4      5      4      5      5
##    198    199    200    201    202    203    204    205    206    207    208    209    210    211    212    213
##     7      4      5      2      7      7      4      6      6     10     5     11     3      6      6      2
##    214    215    216    217    218    219    220    221    222    223    224    225    226    227    228    229
##     3      5      4      5      7      5      4      3      4      7      4      4      3      9      5      5
##    230    231    232    233    234    235    236    237    238    239    240    241    242    243    244    245
##     8      3      5      3      2      5      5      6      3      3      5      5      4      3      7      4
##    246    247    248    249    250    251    252    253    254    255    256    257    258    259    260    261
##     2      3      3      2      2      4      3      1      3      2      2      5      2      3      2      4
##    262    264    265    266    267    268    269    270    271    272    273    274    275    276    277    278
##     3      5      1      2      6      2      6      6      4      3      2      3      5      5      1      1
##    280    281    282    283    284    285    286    287    288    289    290    291    292    293    295    296
##     6      4      7      6      1      4      3      6      4      2      6      5      1      2      3      3
```

```

## 297 298 299 300 301 302 303 304 305 306 307 308 309 310 311 312
## 1 2 5 2 1 1 2 5 3 3 2 1 1 2 2 5
## 313 315 316 317 318 319 320 321 322 323 325 326 327 328 330 331
## 4 2 2 3 2 2 1 1 3 1 2 1 1 1 1 2
## 333 334 335 336 337 338 339 340 342 343 344 346 347 348 349 351
## 1 1 1 1 2 2 5 4 4 2 2 3 3 2 1 1
## 353 354 355 356 357 358 359 360 361 362 363 364 366 367 368 371
## 3 1 2 4 2 1 2 1 1 3 1 2 1 1 2 3
## 372 377 378 379 380 381 382 383 384 385 387 390 391 392 393 400
## 1 1 4 1 3 2 1 2 1 2 2 2 5 1 6 1
## 402 405 406 407 408 409 410 411 412 413 415 417 418 421 423 424
## 1 2 3 1 2 1 1 2 1 2 1 1 2 1 1 1
## 427 428 430 431 432 433 434 435 436 437 439 441 442 445 447 448
## 1 2 3 1 1 1 1 1 5 3 2 1 1 2 3 2
## 450 451 453 455 458 459 462 467 469 470 471 472 476 477 479 480
## 1 4 2 3 1 3 1 2 1 1 2 1 1 3 1 1
## 485 486 487 488 490 492 493 494 495 497 498 499 501 502 518 527
## 1 3 2 1 1 1 1 2 1 1 2 1 2 1 1 2
## 530 534 538 544 548 549 550 558 559 560 566 569 571 573 575 576
## 3 2 2 1 1 1 1 2 2 1 1 1 1 1 1 1
## 584 588 606 617 623 632 652 668 671 677 680 681 685 691 695 698
## 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2
## 706 709 715 718 740 753 767 823 862 899 979 1025 1026
## 1 1 1 1 1 1 1 1 1 1 1 1 1
##
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 6.00 26.00 54.00 92.41 115.00 1026.00
##
## includes extended item information - examples:
## labels
## 1 1000001
## 2 1000002
## 3 1000003

```

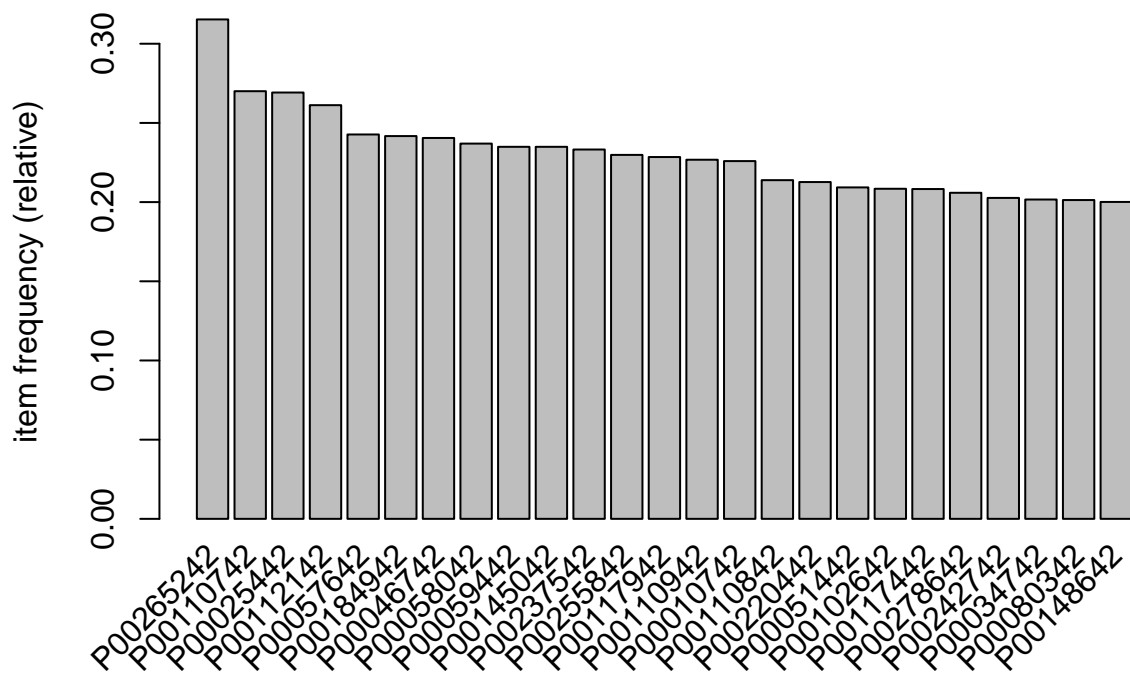
Interpretation of the “*element length distribution*” is accurate. The mean value of 92.41 indicates the average number of items in a customer’s basket. However, considering the presence of customers who purchased a significantly larger number of items, the median value of 54.00 items can provide a more representative measure of the central tendency of the distribution.

Using the median value to assess the typical number of items per customer is a prudent approach, as it is less influenced by outlier values and provides a more balanced representation of the dataset. To create an item frequency plot using the *arules* package, use the following code:

```

itemFrequencyPlot(customersProducts, topN = 25) # topN is limiting to the top 50 products

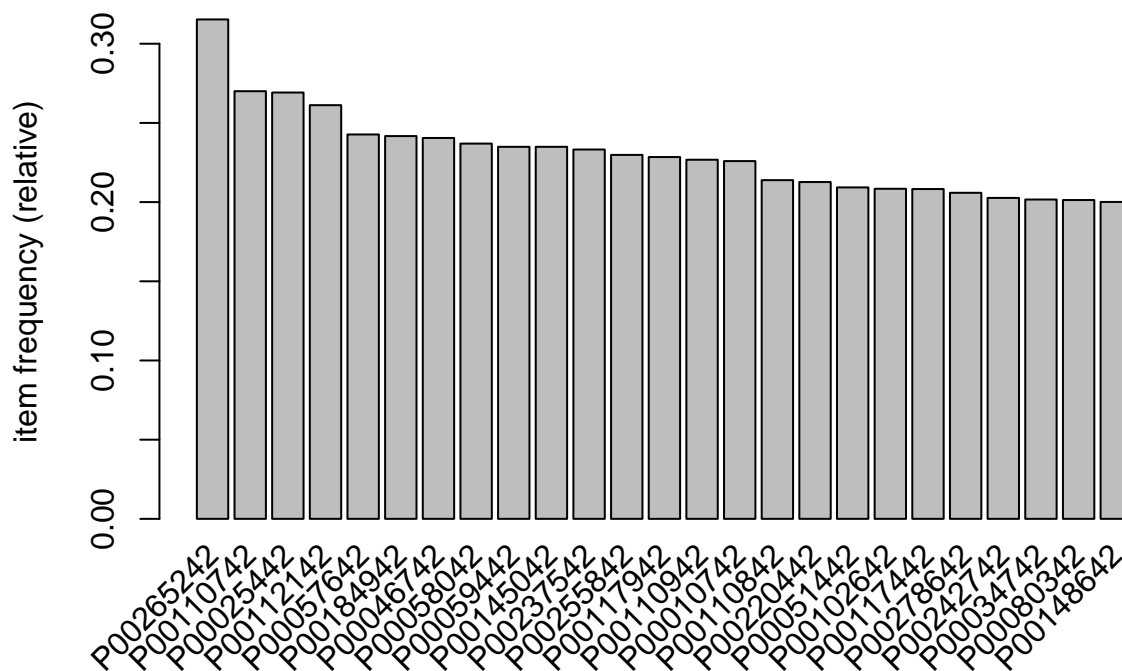
```



In this code, `itemFrequencyPlot()` generates a bar plot that displays the frequency of each item's occurrence in the transactions data. The support parameter specifies the minimum level of support an item should have to be included in the plot, and the `col` parameter sets the color of the bars in the plot.

This plot will visually illustrate the frequency distribution of different items in customer baskets, providing insights into the most commonly purchased products. As continue with analysis, delving deeper into the transactional patterns of customers, gaining a richer understanding of their shopping behaviors. If further questions or if ready to explore the results of the Apriori algorithm.

```
itemFrequencyPlot(customersProducts, topN = 25)    # topN is limiting to the top 50 products
```



Explanation of setting the parameters for the Apriori algorithm is clear and accurate. The choice of support and confidence values plays a critical role in determining the rules generated by the algorithm.

These values guide the algorithm to identify significant associations between items based on the frequency of occurrence and the strength of the relationship. Setting the support value involves establishing a minimum threshold for the number of transactions that an item must be present in. This threshold helps filter out less frequent items that may not contribute significantly to meaningful rules.

In this example, aim to select products that were purchased by at least 50 different customers, and calculate the support value as a ratio of this threshold to the total number of transactions. Similarly, the confidence value serves as a threshold for the strength of the rule's prediction.

A higher confidence value ensures that the rules generated are more likely to be accurate and relevant. Starting with a default confidence value of 0.80 and then adjusting it based on domain knowledge and the desired outcome is a pragmatic approach. Step-by-step approach to selecting these parameters reflects a thoughtful process of refining the algorithm's behavior to yield valuable insights that align with analysis goals.

As a move forward with implementing the Apriori algorithm using these parameters, paving the way to uncovering significant associations among purchased items. This analysis will aid in optimizing product placement, recommendations, and promotional strategies for the retail store.

```
rules = apriori(data = customersProducts,
                parameter = list(support = 0.008, confidence = 0.80,
                                maxtime = 0))
```

```
## Apriori
##
## Parameter specification:
```



```
## confidence minval smax arem aval originalSupport maxtime support minlen
##      0.8    0.1    1 none FALSE          TRUE      0  0.008      1
## maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
## filter tree heap memopt load sort verbose
##      0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 47
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[10539 item(s), 5892 transaction(s)] done [0.11s].
## sorting and recoding items ... [2099 item(s)] done [0.01s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 6 done [15.08s].
## writing ... [7 rule(s)] done [0.28s].
## creating S4 object ... done [0.20s].
```

```
# maxtime = 0 will allow our algorithm to run until completion with
# no time limit
```

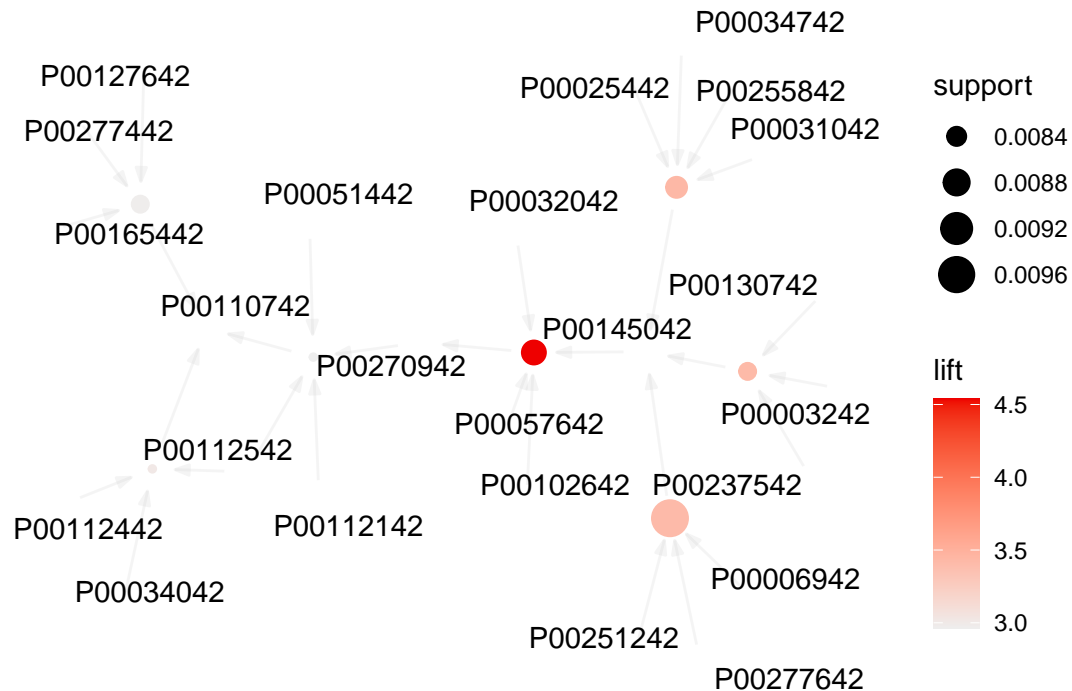
It looks like apriori has created 7 rules in accordance to specified parameters. “writing ... [7 rule(s)] done [0.48s].” Now, lets examine results to get a better idea of how algorithm worked.

```
inspect(sort(rules, by = 'lift'))
```

	lhs	rhs	support	confidence	coverage	lift	count
## [1]	{P00032042,						
##	P00057642,						
##	P00102642,						
##	P00145042}	=> {P00270942}	0.008655804	0.8793103	0.009843856	4.540663	51
## [2]	{P00025442,						
##	P00031042,						
##	P00034742,						
##	P00255842}	=> {P00145042}	0.008486083	0.8064516	0.010522743	3.433246	50
## [3]	{P00003242,						
##	P00130742,						
##	P00237542}	=> {P00145042}	0.008316361	0.8032787	0.010353021	3.419738	49
## [4]	{P00006942,						
##	P00251242,						
##	P00277642}	=> {P00145042}	0.009674134	0.8028169	0.012050238	3.417773	57
## [5]	{P00034042,						
##	P00112442,						
##	P00112542}	=> {P00110742}	0.008146640	0.8135593	0.010013578	3.012880	48
## [6]	{P00127642,						
##	P00165442,						
##	P00277442}	=> {P00110742}	0.008316361	0.8032787	0.010353021	2.974807	49
## [7]	{P00051442,						
##	P00112142,						
##	P00112542,						
##	P00270942}	=> {P00110742}	0.008146640	0.8000000	0.010183299	2.962665	48

Here see the association rules created by apriori algorithm. Let's take a look at rule number 1. Description of the output values of the Apriori algorithm is accurate and well-organized. Provided a clear explanation of each value and its significance in the context of the association rules generated by the algorithm. Here's how visualize these rules using the arulesViz package:

```
plot(rules, method = 'graph')
```



The plot() function with the method parameter set to “scatterplot” generates a scatterplot that displays the relationship between support, confidence, and lift for each rule. This visualization can help quickly grasp the distribution of rules and their characteristics, aiding in the identification of meaningful and impactful associations.

Continuing analysis by visualizing the generated association rules using the arulesViz package adds another layer of understanding to insights. By visually representing these rules, providing a more accessible and intuitive view of the complex relationships within the dataset.

To proceed with the visualization step, and if have any further questions or if ready to interpret the results of the association rules, I'm here to assist!

```
rules = apriori(data = customersProducts,
                parameter = list(support = 0.008, confidence = 0.75, maxtime = 0))
```

```
## Apriori
##
## Parameter specification:
## confidence minval smax arem aval originalSupport maxtime support minlen
```

```
##      0.75    0.1    1 none FALSE          TRUE      0    0.008      1
## maxlen target ext
##      10 rules TRUE
##
## Algorithmic control:
## filter tree heap memopt load sort verbose
##      0.1 TRUE TRUE  FALSE TRUE      2      TRUE
##
## Absolute minimum support count: 47
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[10539 item(s), 5892 transaction(s)] done [0.12s].
## sorting and recoding items ... [2099 item(s)] done [0.01s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 6 done [15.98s].
## writing ... [171 rule(s)] done [0.33s].
## creating S4 object ... done [0.27s].
```

Now that decreased the minimum confidence value to 75%, a total of 171 rules. This is much higher number of rules compared to previous rule list which only contained 7. This should now give us more interesting rules to examine.

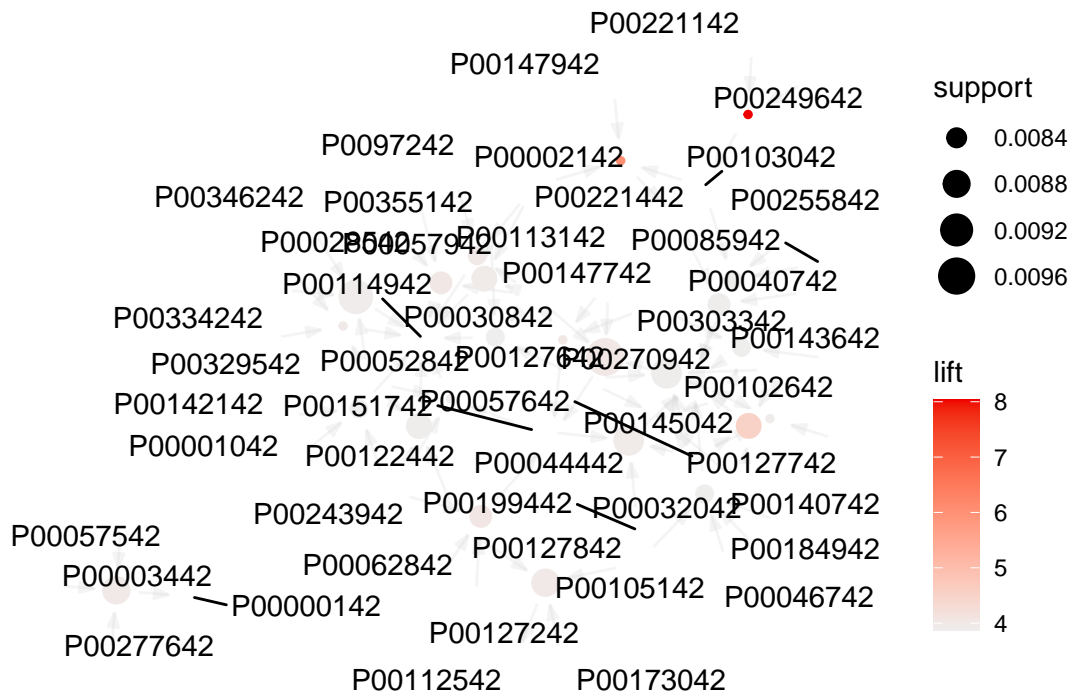
```
inspect(head(sort(rules, by = 'lift')) # limiting to the top 6 rules
```

```
##      lhs                rhs          support confidence    coverage    lift count
## [1] {P00221142,
##      P00249642} => {P00103042} 0.008146640 0.7619048 0.010692464 8.030667    48
## [2] {P00002142,
##      P00103042,
##      P00147942} => {P00221442} 0.008146640 0.7500000 0.010862186 6.045144    48
## [3] {P00032042,
##      P00057642,
##      P00102642,
##      P00145042} => {P00270942} 0.008655804 0.8793103 0.009843856 4.540663    51
## [4] {P00062842,
##      P00127242,
##      P00243942} => {P00044442} 0.008486083 0.7575758 0.011201629 4.061544    50
## [5] {P00030842,
##      P00057942,
##      P00355142} => {P00114942} 0.008486083 0.7936508 0.010692464 4.024260    50
## [6] {P00030842,
##      P00147742,
##      P00303342} => {P00044442} 0.008146640 0.7500000 0.010862186 4.020928    48
```

A new set of rules and the rule with the highest lift value has also changed. Rule number 1 shows that Customers who bought items P00221142 and P00249642 will also purchase item P00103042 ~76% of the time, given a support of 0.008.

```
plot(rules, method = 'graph', max = 25)
```

```
## Warning: Too many rules supplied. Only plotting the best 25 using 'lift'
## (change control parameter max if needed).
```

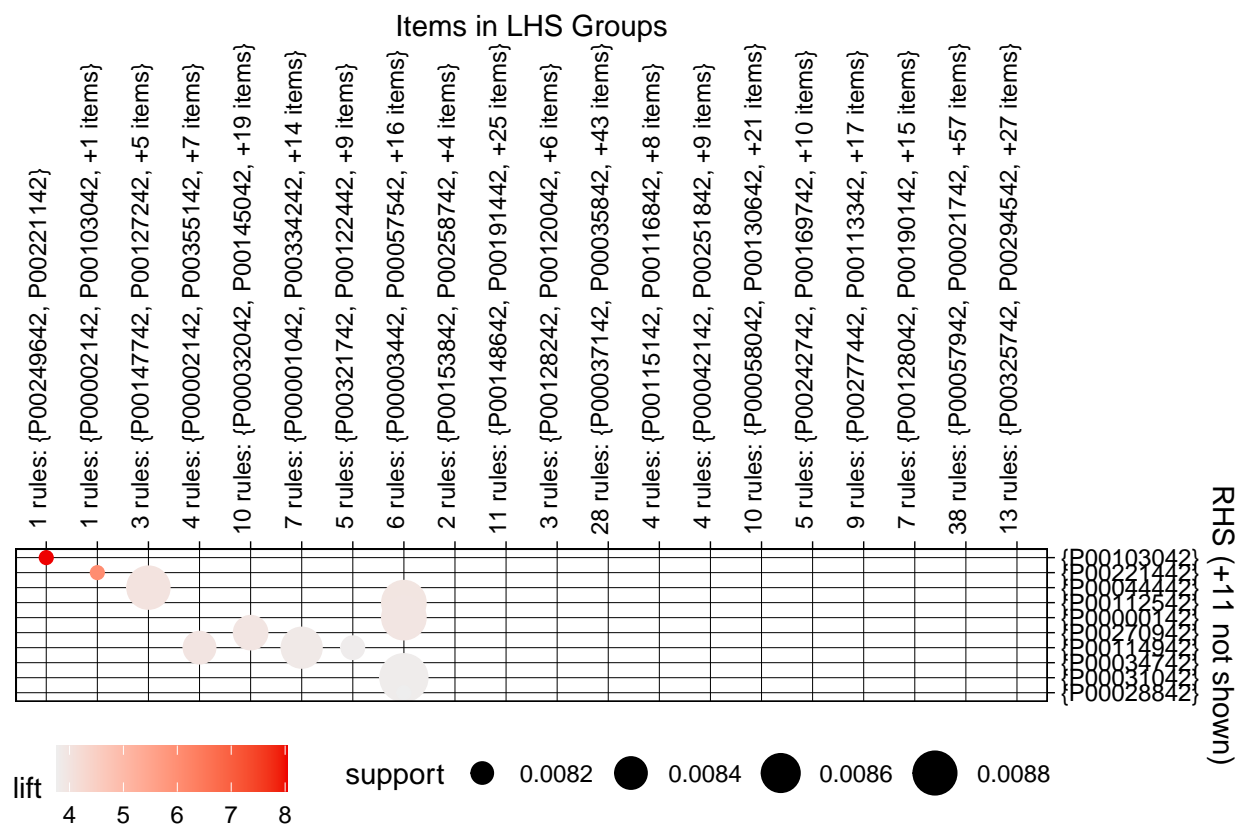


Now that 7 rules, this visualization becomes a lot more difficult to interpret. Instead, create a matrix and have a similar plot and clearer interpretation.

```
plot(rules, method = 'grouped', max = 25)
```

```
## Warning: Unknown control parameters: max
```

```
## Available control parameters (with default values):
## k      = 20
## aggr.fun = function (x, ...) UseMethod("mean")
## rhs_max = 10
## lhs_label_items = 2
## col     = c("#EE0000FF", "#EEEEEEFF")
## groups  = NULL
## engine  = ggplot2
## verbose = FALSE
```



In this visualization, can see that LHS on top and on the right hand side, the corresponding RHS. The size of the bubbles represents the support value of the rule and the fill/color represents the lift.

5 Chapter 5

5.1 Conclusion

Summary provides a comprehensive overview of the key insights and discoveries that made from Exploratory Data Analysis (EDA) and Association Rule Learning (ARL) analysis of the Black Friday dataset. The Analysis have effectively highlighted the important aspects of analysis, from customer distribution across different categories to identifying top customers, product classifications, and various purchase metrics.

In the context of Association Rule Learning, highlighted the significance of discovering associations among items and how these insights can be leveraged by retailers to optimize product placement, recommendations, and marketing strategies. Summary effectively captures the essence of analytical journey, showcasing meticulous exploration of the dataset and the valuable insights extracted.

This kind of summary is not only informative but also demonstrates the depth and quality of analysis to others, might be interested in findings. The Exploratory Data Analysis (EDA) and Association Rule Learning (ARL) analysis of the Black Friday dataset have yielded valuable insights, providing a comprehensive understanding of customer behavior and purchase patterns. The analysis has successfully covered a range of critical aspects, including customer distribution across different categories, identification of top customers, product classifications, and various purchase metrics.

In the realm of EDA, the analysis showcased meticulous exploration of the dataset, uncovering significant trends and relationships. The distribution of customers across categories was thoroughly examined, shedding light on preferences and trends. The identification of top customers contributes to a nuanced understanding of high-value segments. Additionally, the analysis delved into product classifications, offering a detailed perspective on the product landscape and its implications for sales and marketing strategies.

The Association Rule Learning analysis emphasized the importance of discovering associations among items. Insights derived from this analysis can be leveraged by retailers to optimize product placement, enhance recommendations, and refine marketing strategies. The potential impact of these findings on retail operations is substantial, as retailers can strategically position products and tailor marketing efforts based on observed associations among items.

5.1.1 Key Findings

The analysis illuminated significant aspects of the dataset:

1. ****Customer Demographics:**** Gender and age-specific insights reveal that while male shoppers dominate in numbers, female shoppers demonstrate comparable average spending, suggesting they are a high-value customer segment. The age group 26-35 emerged as the most influential demographic in terms of purchasing behavior.
2. **Regional Trends:** City B exhibited the highest total purchase values, though City C had a larger customer base, indicating potential for optimizing sales strategies by balancing transaction frequency and product value.
3. **Product Trends:** The study identified top-selling products, including the best-seller (P00265242), which exhibited consistent popularity across demographics. Pricing discrepancies likely influenced by regional discounts and promotions present an opportunity for retailers to refine pricing strategies.
4. **Association Rule Learning:** ARL revealed actionable associations among products, providing a foundation for strategic decisions in product bundling, inventory optimization, and targeted marketing.

5.1.2 Actionable Insights

1. **Demographic-Based Promotions:** Gender-specific deals for female shoppers and personalized recommendations for high-value age groups like 26-35.

2. **Regional Strategies:** High-value products in City B and frequency-driven promotions in City C to balance revenue.
3. **Product Bundling:** Use Apriori insights to create product bundles that reflect frequently purchased itemsets, enhancing customer satisfaction and sales.

5.1.3 Deeper Explanation of Trends

Ser	Trends	Observation	Interpretation	Potential Impact
1	Gender-Based Trends	Male shoppers outnumber female shoppers significantly, but the average spending of females is closer to that of males	This indicates that while fewer in number, female shoppers are high-value customers. Retailers might focus on strategies like personalized promotions for female shoppers to enhance their shopping experience	Targeted campaigns, especially during high-traffic periods like Black Friday, could maximize sales
2	Age-Based Trends	The 26-35 age group dominates in both the overall data set and the best-selling product category	This age group likely represents the working demographic with higher disposable incomes, making them the primary market for promotions.	Retailers can create marketing campaigns or bundle deals specifically designed for this age group to increase engagement
3	City-Based Trends	City B has the highest purchase amount despite City C having more shoppers.	This suggests that shoppers in City B are making fewer but higher-value purchases, possibly influenced by income levels or product availability.	Tailoring inventory for high-value products in City B and focusing on increasing transaction frequency in City C could optimize revenue.
4	Top Sellers and Product Trends	The best-selling product (P00265242) is uniformly popular across demographics but has varying purchase prices.	Price variations could result from regional promotions, discounts, or coupon codes. This variability suggests opportunities to optimize pricing strategies.	Analyzing the effectiveness of pricing strategies across regions could enhance profit margins.

5.1.4 Limitations of the Analysis

However, it is crucial to acknowledge the limitations of the analysis. The insights generated are based on the available data, and the findings may not be universally applicable to all retail contexts. Furthermore, the analysis may be sensitive to data quality, and any inaccuracies or biases in the dataset could impact the robustness of the results.

5.1.5 Future Work

Looking ahead, future work could focus on expanding the dataset to include more diverse and granular information. Additionally, refining the models used in the analysis and exploring advanced techniques could further enhance the accuracy and depth of insights. Incorporating external factors, such as economic indicators or seasonal trends, could also provide a more holistic understanding of consumer behavior during Black Friday or other sales events.

In conclusion, the report's summary effectively captures the depth and quality of the analytically journey, showcasing not only the informative nature of the findings but also the potential implications for retailers. While recognizing the limitations, the report sets the stage for future research and improvements in methodology, ensuring a continuous and evolving understanding of consumer behavior in the context of Black Friday sales.

This report highlights the value of data-driven analysis in retail strategy development, particularly for high-impact sales events like Black Friday. By addressing the identified limitations and pursuing the proposed future directions, this study can evolve into a robust framework for comprehending and leveraging consumer behavior.

6 Reference

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7 Appendix

7.1 Packages

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