# Wholesale Customer Dataset Evaluation

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#### Introduction

The UCI Wholesale customers dataset is provided by the University of California at Irvine, it refers to clients of a wholesale distributor. It includes the annual spending in monetary units (m.u.) on diverse product categories. What we are doing today is using this data to analyze some customer spending patterns and derive some insights.

### Step 1: Load the Dataset

## Rows: 440 Columns: 8

First, we load the "Wholesale customers" dataset into R. This dataset has information on annual spending in various product categories by different customers. You can download it from Kaggle:

```
# Install and load necessary packages
install.packages("readr")
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.4'
## (as 'lib' is unspecified)
install.packages("ggplot2")
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.4'
## (as 'lib' is unspecified)
install.packages("scales")
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.4'
## (as 'lib' is unspecified)
install.packages("knitr")
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.4'
## (as 'lib' is unspecified)
library(readr)
library(ggplot2)
library(scales)
##
## Attaching package: 'scales'
## The following object is masked from 'package:readr':
##
##
       col_factor
library(knitr)
# Load the dataset
wholesale_data <- read_csv("Wholesale customers data.csv")</pre>
```

```
## -- Column specification -----
## Delimiter: ","
## dbl (8): Channel, Region, Fresh, Milk, Grocery, Frozen, Detergents_Paper, De...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
head(wholesale_data) # Check the first few rows
## # A tibble: 6 x 8
##
    Channel Region Fresh Milk Grocery Frozen Detergents_Paper Delicassen
       <dbl> <dbl> <dbl> <dbl> <
##
                                 <dbl> <dbl>
                                                          <dbl>
                                                                    <dbl>
## 1
          2
                 3 12669 9656
                                  7561
                                          214
                                                          2674
                                                                     1338
## 2
          2
                                  9568
                 3 7057 9810
                                         1762
                                                          3293
                                                                     1776
          2
## 3
                 3 6353 8808
                                  7684
                                         2405
                                                          3516
                                                                     7844
## 4
          1
                 3 13265 1196
                                  4221
                                         6404
                                                           507
                                                                     1788
## 5
          2
                 3 22615 5410
                                  7198
                                         3915
                                                          1777
                                                                     5185
## 6
          2
                 3 9413 8259
                                  5126
                                          666
                                                          1795
                                                                     1451
```

#### Step 2: Data Cleaning and Transformation

Next, let's clean the data to ensure it is ready for analysis:

```
# Check for missing values
sum(is.na(wholesale_data)) # Check for any NA values

## [1] 0

# Transform data if necessary
# In this dataset, ensure relevant columns are numeric
wholesale_data$Channel <- as.factor(wholesale_data$Channel)
wholesale_data$Region <- as.factor(wholesale_data$Region)

# Create a new variable for total annual spending
wholesale_data$TotalSpending <- rowSums(wholesale_data[, c("Fresh", "Milk", "Grocery", "Frozen", "Deter</pre>
```

## Step 3: Data Aggregation

Now, let's aggregate the data to get insights into customer spending patterns:

```
# Aggregate total spending by region
spending_by_region <- aggregate(TotalSpending ~ Region, data = wholesale_data, sum)

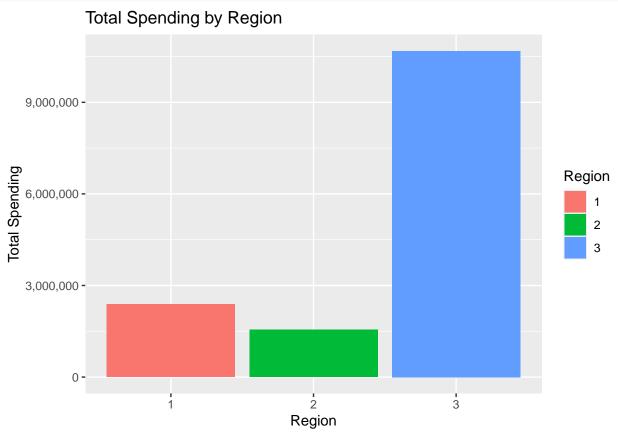
# Aggregate total spending by channel
spending_by_channel <- aggregate(TotalSpending ~ Channel, data = wholesale_data, sum)

# Get the average spending per category
average_spending_per_category <- sapply(wholesale_data[, c("Fresh", "Milk", "Grocery", "Frozen", "Determine total spending per_category ("Frozen", "Frozen", "Determine total spending per_category ("Frozen", "Frozen", "Determine total spending per_category ("Frozen", "Frozen", "Determine total spending per_category ("Frozen", "Frozen", "Frozen", "Determ
```

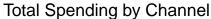
#### Step 4: Data Visualization

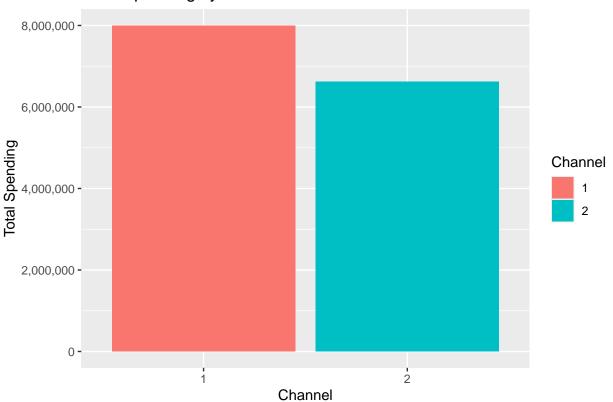
Then we will use ggplot2 to create visualizations to better understand the data:

```
# Bar plot of total spending by region
ggplot(spending_by_region, aes(x = Region, y = TotalSpending, fill = Region)) +
geom_bar(stat = "identity") +
labs(title = "Total Spending by Region", x = "Region", y = "Total Spending")+
scale_y_continuous(labels = comma)
```



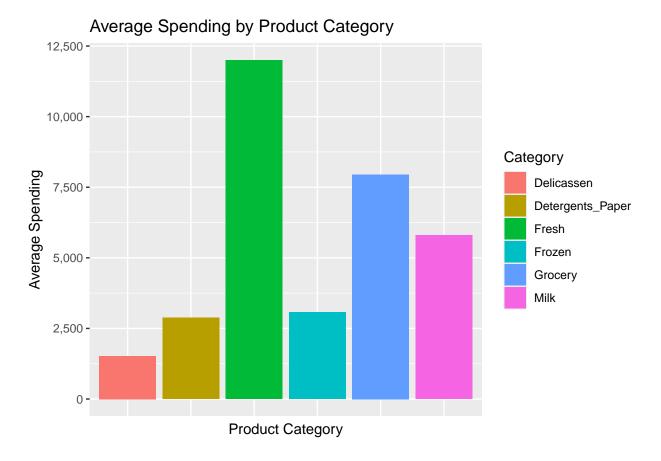
```
# Bar plot of total spending by channel
ggplot(spending_by_channel, aes(x = Channel, y = TotalSpending, fill = Channel)) +
geom_bar(stat = "identity") +
labs(title = "Total Spending by Channel", x = "Channel", y = "Total Spending")+
scale_y_continuous(labels = comma)
```





```
# Bar plot of average spending by product category
average_spending_df <- data.frame(Category = names(average_spending_per_category), AverageSpending = av

ggplot(average_spending_df, aes(x = Category, y = AverageSpending, fill = Category)) +
    geom_bar(stat = "identity") +
    labs(title = "Average Spending by Product Category", x = "Product Category", y = "Average Spending")
    theme(axis.text.x=element_blank(),
        axis.ticks.x=element_blank())+
    scale_y_continuous(labels = comma)</pre>
```



## Conclusion

Looking at the first plot, we can see that there is a substantial amount more sales in Region 3, classified as "other" in the dataset. Meaning we should probably focus our marketing effort more on the Lisnon and Oporto regions in an attempt raise sales in those regions. What we do not know is how many regions are being initially aggregated to form the "other" category, we may want to investigate that further to understand more about how individual regions are performing. Looking at the second chart, we see that there is about 20% more sales via Channel 1 (hotel/restaurant/cafe) than Channel 2 (retail). Investigating this further we can see that Channel 1 is aggregating hotel, restaurant and cafe sales into one category so that may be a reason why the sales for that channel is higher in aggregate sales. The third chart is showing us that our average fresh sales are significantly more than any other category of product that we sell. Delicatessen products have the least average sales by a significant amount. Delicatessen product sales are at about 1000 average sales units, while fresh product sales are at about 11,500 average sales units. Using this data I would recommend that the company focus on delicatessen, detergent, and frozen product sales in their marketing efforts in an attempt to raise those sales to at least the average.

**Data Citation** Cardoso, Margarida. (2014). Wholesale customers. UCI Machine Learning Repository. https://doi.org/10.24432/C5030X.