Shopify Data science Challenge AOV

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Question

Given some sample data, write a program to answer the following: click here to access the required data set

In Shopify, we have exactly 100 sneaker shops, and each of these shops sells only one model of shoe. We want to do some analysis of the average order value (AOV). When we look at orders data over a 30 day window, we naively calculate an AOV of \$3,145.13. Given that we know these shops are selling sneakers, a relatively affordable item, something seems wrong with our analysis.

- 1. Think about what could be going wrong with our calculation. Think about a better way to evaluate this data.
- 2. What metric would you report for this data set?
- 3. What is its value?

Answer to Question:

- 1. Presence of uutliers in the data set
- 2. AOV without outliers
- 3. AOV: \$299 dollars

Approach

Here are the list of steps I intend to use to evaluate if the AOV is a good measurement or not:

- Investigating the data set: Visually understanding the data and look for (filter) outliers.
- Observe how AOV vary with and without outliers

Load Libraries and Data

head(data)

```
## # A tibble: 6 x 7
##
     order_id shop_id user_id order_amount total_items payment_method created_at
##
        <dbl>
                 <dbl>
                          <dbl>
                                                     <dbl> <chr>
                                        <dbl>
                                                                            <chr>
## 1
             1
                    53
                            746
                                          224
                                                         2 cash
                                                                            2017-03-13 1~
             2
## 2
                    92
                            925
                                           90
                                                                           2017-03-03 1~
                                                         1 cash
## 3
             3
                    44
                            861
                                          144
                                                         1 cash
                                                                           2017-03-14 4~
## 4
             4
                    18
                            935
                                          156
                                                         1 credit_card
                                                                           2017-03-26 1~
## 5
             5
                    18
                            883
                                          156
                                                         1 credit_card
                                                                           2017-03-01 4~
             6
## 6
                    58
                            882
                                          138
                                                         1 credit_card
                                                                           2017-03-14 1~
```

Data Cleaning

Change the data type of some of the columns for easier manipulation

```
data <- data |>
  mutate(order_id = as.factor(order_id))|>
  mutate(shop_id = as.factor(shop_id))|>
  mutate(user_id = as.factor(user_id))|>
  mutate(payment_method = as.factor(payment_method))|>
  mutate(created_at = as.Date(created_at))
data
## # A tibble: 5,000 x 7
      order_id shop_id user_id order_amount total_items payment_method created_at
               <fct>
                                                   <dbl> <fct>
##
      <fct>
                       <fct>
                                       <dbl>
                                                                         <date>
##
   1 1
                       746
                                                                         2017-03-13
               53
                                         224
                                                       2 cash
##
  2 2
               92
                       925
                                          90
                                                       1 cash
                                                                         2017-03-03
##
  3 3
               44
                       861
                                         144
                                                       1 cash
                                                                         2017-03-14
## 4 4
               18
                       935
                                                       1 credit_card
                                                                         2017-03-26
                                         156
## 5 5
               18
                       883
                                         156
                                                       1 credit_card
                                                                         2017-03-01
##
  6 6
               58
                       882
                                                       1 credit_card
                                         138
                                                                         2017-03-14
##
  7 7
               87
                       915
                                         149
                                                       1 cash
                                                                         2017-03-01
## 88
               22
                       761
                                         292
                                                       2 cash
                                                                         2017-03-08
## 9 9
               64
                       914
                                         266
                                                       2 debit
                                                                         2017-03-17
## 10 10
               52
                       788
                                         146
                                                       1 credit_card
                                                                         2017-03-30
## # ... with 4,990 more rows
```

Investigating the data set

•

$$\label{eq:Calculate unit cost} \begin{aligned} \text{Calculate unit cost} &= \frac{\text{Order Amount}}{\text{Total Items}} \end{aligned}$$

•

$$AOV = \frac{Summed\ Order\ Amount}{Number\ of\ Orders}$$

```
AOV <- sum(data$order_amount)/ nrow(data)
AOV
```

```
## [1] 3145.128
```

2 78

Expectation: I assume that the distribution of the AOV is not skewed . My assumption is from the question "the stores sell the same kind of sneakers".

Plotting AOV per Shop

49213.

I am going to create the AOV per shop. The table below shows the aov in each shop.

The AOV at shops 42 and 78 is very high approximately 235, 101 dollars and 49,213 dollars respectively.

```
shop_aov <- data |>
  group_by(shop_id = as.factor(shop_id))|>
  summarise(aov = sum(order_amount)/ n())|>
  arrange(desc(aov))
shop_aov

## # A tibble: 100 x 2
## shop_id aov
## <fct> <dbl>
## 1 42 235101.
```

```
3 50
                   404.
##
                   403.
##
    4 90
    5 38
##
                   391.
    6 81
                   384
##
##
    7 6
                   384.
##
    8 89
                   379.
##
    9 33
                   376.
## 10 51
                   362.
## # ... with 90 more rows
```

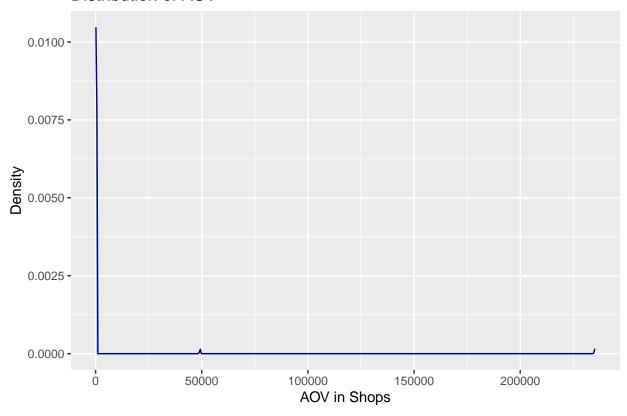
Distribution of AOV

The plot below shows that most of the shops have a low AOV and few have high AOV. These are the little peaks at around 50,000 and above 200,000

Result: The plot below proves that the shops are not selling the sneakers at a normally distributed price. The plot is right skewed. This indicates presence of outliers in the data.

```
shop_aov |>
    ggplot(aes(x= aov)) +
    geom_density(color="darkblue", fill="lightblue") +
    ggtitle('Distribution of AOV') +
    ylab('Density') +
    xlab('AOV in Shops')
```

Distribution of AOV



Next, I will remove the outliers in the data

```
outliers <- boxplot(shop_aov$aov, plot = FALSE)$out
paste0("NUmbers of Outliers: ", length(outliers))</pre>
```

Removing Outliers

```
## [1] "NUmbers of Outliers: 2"
shop_aov_clean <- shop_aov[!(shop_aov$aov %in% outliers), ]
#shop_aov_clean</pre>
```

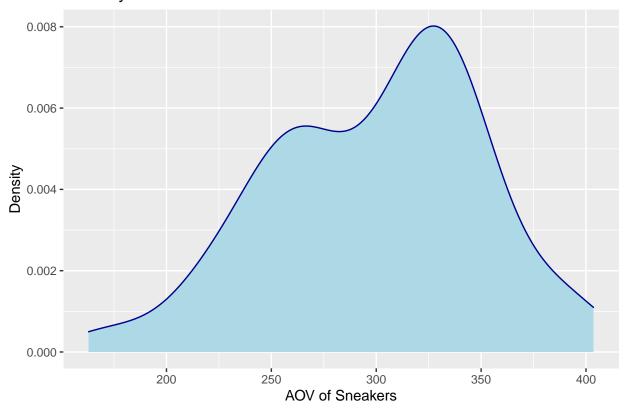
I will reproduce the two plot above to see if removing outliers has an effect on **unit cost**, hence have an effect on **AOV**.

Observation

There are two peaks in the distributions. This could indicate two groups in the shops. Overall, this is a better distribution than the first

```
shop_aov_clean |>
    ggplot(aes(x= aov)) +
    geom_density(color="darkblue", fill="lightblue") +
    ggtitle('Dernsity Distribution of AOV: Without Outliers ') +
    ylab('Density') +
    xlab('AOV of Sneakers')
```

Dernsity Distribution of AOV: Without Outliers



Calculate average AOV after Outlier removal The AOV drastically reduced from \$3,145 to \$299.6 dollars. AOV is easily affected by outliers. In this dataset, if outliers are removed, AOV would be a good

metric

```
AOV_no_outlier <- mean(shop_aov_clean$aov)
AOV_no_outlier
```

[1] 299.6824

Answer to the Questions;

1.

Comments

- AOV is a good metric but sensitive to outliers. It's however possible that the outliers in the data are not as a result of data entry error. Some stores might be owned by a celebrity and people would love to buy from them. Hence the high order amount.
- What should matter to the store is if they are able to retain customers. Given the time period of the data set, it would be difficult to calculate customer retention form scratch.