# Shopify Winter 2022 Data Science Challenge by Oliver Pan

## Question 1

Before we begin, let's take a look at our data and the problem we are trying to solve.

### Import data & libraries

In [60]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statistics
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [61]:
```
sneakers_data = pd.read_csv(r'C:\Users\Oliver\Desktop\winter.csv')
```

### Exploratory Data Analysis (EDA)

In [62]:
```
# Quick look at the dataset
sneakers_data.head()
```

Out[62]:

| | order_id | shop_id | user_id | order_amount | total_items | payment_method | created_at |
|---|---|---|---|---|---|---|---|
| 0 | 1 | 53 | 746 | 224 | 2 | cash | 2017-03-13 12:36:56 |
| 1 | 2 | 92 | 925 | 90 | 1 | cash | 2017-03-03 17:38:52 |
| 2 | 3 | 44 | 861 | 144 | 1 | cash | 2017-03-14 4:23:56 |
| 3 | 4 | 18 | 935 | 156 | 1 | credit_card | 2017-03-26 12:43:37 |
| 4 | 5 | 18 | 883 | 156 | 1 | credit_card | 2017-03-01 4:35:11 |

In [63]:
```
# Check to ensure we are seeing all columns
sneakers_data.columns
```

Out[63]:
```
Index(['order_id', 'shop_id', 'user_id', 'order_amount', 'total_items',
       'payment_method', 'created_at'],
      dtype='object')
```

In [64]:
```
# Check the structure of the dataset
sneakers_data.shape
```

Out[64]:
```
(5000, 7)
```

In [65]:
```
# Viewing descriptive statistics of two columns
sneakers_data[['order_amount', 'total_items']].describe()
```

Out[65]:

| | order_amount | total_items |
|---|---|---|
| count | 5000.000000 | 5000.00000 |
| mean | 3145.128000 | 8.78720 |
| std | 41282.539349 | 116.32032 |
| min | 90.000000 | 1.00000 |
| 25% | 163.000000 | 1.00000 |
| 50% | 284.000000 | 2.00000 |
| 75% | 390.000000 | 3.00000 |
| max | 704000.000000 | 2000.00000 |

Just as we suspected, the average order_amount seems to be quite high, given that shoes are affordable. Let's investigate a bit more to see why that might be.

In [66]:
```
# Ensure no NULL data
null_check = sneakers.isnull().sum().to_frame()
null_check.columns = ['number_null']
null_check
```

Out[66]:

| | number_null |
|---|---|
| order_id | 0 |
| shop_id | 0 |
| user_id | 0 |
| order_amount | 0 |
| total_items | 0 |
| payment_method | 0 |
| created_at | 0 |

After our EDA, we can now start with our resolutions to this analysis problem

## a. Think about what could be going wrong with our calculation. Think about a better way to evaluate this data.

### Observations

- It seems like our data is skewed, as mentioned previously.
- Often when looking at averages, one anomaly can often make the data appear different.
- We also see further evidence when we see the standard deviation, which measures variability across data

#### Hence, let's look at another way to evaluate this data

### Proposal: Remove Anomalies

In [67]:
```
# Make 2 copies to work with
sneakers_p1 = sneakers_data.copy()
sneakers_p2 = sneakers_data.copy()
```

Before we remove anomalies, I want to scale the purchases to 1 item, to get a better understanding of order_amount

In [68]:
```
# Filter necessary columns for analysis
sneakers_p1 = sneakers_p1[['shop_id', 'order_amount', 'total_items']]
```

In [69]:
```
# Scale purchases to give even weight to total_items
sneakers_p1['orders_to_one'] = sneakers_p1['order_amount'] / sneakers_p1['total_items']
```

In [70]:
```
sneakers_p1.head()
```

Out[70]:

| | shop_id | order_amount | total_items | orders_to_one |
|---|---|---|---|---|
| 0 | 53 | 224 | 2 | 112.0 |
| 1 | 92 | 90 | 1 | 90.0 |
| 2 | 44 | 144 | 1 | 144.0 |
| 3 | 18 | 156 | 1 | 156.0 |
| 4 | 18 | 156 | 1 | 156.0 |

In [71]:
```
sneakers_p1[['orders_to_one']].describe()
```

Out[71]:

| | orders_to_one |
|---|---|
| count | 5000.000000 |
| mean | 387.742800 |
| std | 2441.963725 |
| min | 90.000000 |
| 25% | 133.000000 |
| 50% | 153.000000 |
| 75% | 169.000000 |
| max | 25725.000000 |

#### Part 1: Shop 78 Analysis (Overpriced)

Let's look at each individual shop since the average is still very high

In [72]:
```
# Group by shop_id, averaging purchases per shop
p1_grouped = sneakers_p1.groupby(sneakers_p1['shop_id'])['orders_to_one'].mean().reset_index().sort_values(by=
p1_grouped.head(10)
```

Out[72]:

| | shop_id | orders_to_one |
|---|---|---|
| 77 | 78 | 25725.0 |
| 41 | 42 | 352.0 |
| 11 | 12 | 201.0 |
| 88 | 89 | 196.0 |
| 98 | 99 | 195.0 |
| 49 | 50 | 193.0 |
| 37 | 38 | 190.0 |
| 50 | 51 | 187.0 |
| 5 | 6 | 187.0 |
| 10 | 11 | 184.0 |

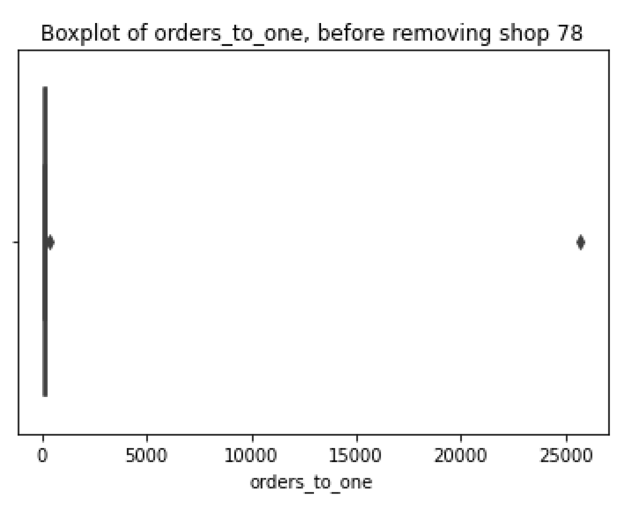
#### Therefore, we reveal that shop 78 is overpricing, as to why the average is still high.

In [73]:
```
# Average before removing shop 78 from calculation
round(np.mean(sneakers_p1['orders_to_one']), 2)
```

Out[73]:
```
387.74
```

In [74]:
```
# Visual Representation of Anomalies
plt.title('Boxplot of orders_to_one, before removing shop 78')
sns.boxplot(p1_grouped['orders_to_one'])
```

Out[74]:
```
<AxesSubplot:title={'center':'Boxplot of orders_to_one, before removing shop 78'}, xlabel='orders_to_one'>
```

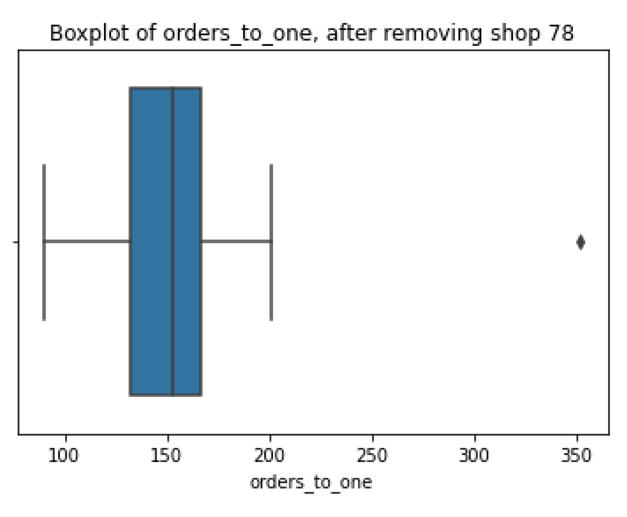



In [75]:
```
# Average after removing shop 78 from calculation
round(np.mean(sneakers_p1[sneakers_p1['shop_id'] != 78]['orders_to_one']), 2)
```

Out[75]:
```
152.48
```

In [76]:
```
plt.title('Boxplot of orders_to_one, after removing shop 78')
sns.boxplot(p1_grouped[p1_grouped['shop_id'] != 78]['orders_to_one'])
```

Out[76]:
```
<AxesSubplot:title={'center':'Boxplot of orders_to_one, after removing shop 78'}, xlabel='orders_to_one'>
```




To conclude, it looks like our shoe is affordable, at an average of $152.48 per shoe across 99 stores

#### Part 2: Shop 42 Analysis (Bulk Sellers)

Let's backtrack once more and look at our dataset previously. One caveat to looking at orders_to_one is that we disregard cases where price seems correct, but amount of shoes_sold is anomalous.

In [18]:
```
sneakers_p2['total_items'].value_counts()
```

Out[18]:
```
2       1832
1       1830
3        941
4        293
5         77
2000      17
6          9
8          1
Name: total_items, dtype: int64
```

#### Which store is selling 2000 items per order?

In [19]:
```
sneakers_p2[sneakers_p2['total_items'] == 2000]['shop_id'].unique()
```

Out[19]:
```
array([42], dtype=int64)
```

#### Is this the shop 42's issue or is it a customer that is driving high order amounts?

In [20]:
```
sneakers_p2 = sneakers_p2[['shop_id', 'user_id', 'order_amount', 'total_items']]
```

In [21]:
```
sneakers_p2[sneakers_p2['shop_id'] == 42].head()
```

Out[21]:

| | shop_id | user_id | order_amount | total_items |
|---|---|---|---|---|
| 15 | 42 | 607 | 704000 | 2000 |
| 40 | 42 | 793 | 352 | 1 |
| 60 | 42 | 607 | 704000 | 2000 |
| 308 | 42 | 770 | 352 | 1 |
| 409 | 42 | 904 | 704 | 2 |

In [22]:
```
sneakers_p2[sneakers_p2['user_id'] == 607].head()
```

Out[22]:

| | shop_id | user_id | order_amount | total_items |
|---|---|---|---|---|
| 15 | 42 | 607 | 704000 | 2000 |
| 60 | 42 | 607 | 704000 | 2000 |
| 520 | 42 | 607 | 704000 | 2000 |
| 1104 | 42 | 607 | 704000 | 2000 |
| 1362 | 42 | 607 | 704000 | 2000 |

The reason we remove shop 42 although the anomalies are caused by customer 607 is because as a business, we cannot control how the consumer spends. We can only change how the business acts, removing this customer to strengthen our model for a better understanding of the problem.

#### After removing both shop 78 and 42.....

In [42]:
```
# Average order amount
round(np.mean(sneakers_p1[(sneakers_p1['shop_id'] != 42) & (sneakers_p1['shop_id'] != 78)])['order_amount'], 2)
```

Out[42]:
```
300.16
```

In [79]:
```
# Average number of items purchased per order
round(np.mean(sneakers_p1[(sneakers_p1['shop_id'] != 42) & (sneakers_p1['shop_id'] != 78)])['total_items'], 3)
```

Out[79]:
```
1.996
```

In [43]:
```
# Scaled to 1 item
round(np.mean(sneakers_p1[(sneakers_p1['shop_id'] != 42) & (sneakers_p1['shop_id'] != 78)])['orders_to_one'], 2
```

Out[43]:
```
150.4
```

Now, we see the data in a better lens. It seems like shoes are much more affordable after data cleansing (removing 2 shops)

## b. What metric would you report for this dataset?

After our previous analysis, we found the average wasn't the best indicator of our analysis. It seems like we weren't considering anomalous situations, which can often skew AOV.

In [27]:
```
# Looking at our order_amount once again
sneakers_data['order_amount'].describe().to_frame().round(2)
```

Out[27]:

| | order_amount |
|---|---|
| count | 5000.00 |
| mean | 3145.13 |
| std | 41282.54 |
| min | 90.00 |
| 25% | 163.00 |
| 50% | 284.00 |
| 75% | 390.00 |
| max | 704000.00 |

Going back, we found that the average order amount is $300.16. This was after we removed our anomolies. But what if there was a situation where we DIDN'T want to remove any data?

- Without any removal of shops, we can look at the data through percentiles.

#### Hence, of the percentiles we look at, 50% or MEDIAN is the metric that would best represent the data.

## c. What is its value?

In [81]:
```
# Median of dataset
np.median(sneakers_data['order_amount'])
```

Out[81]:
```
284.0
```

In [87]:
```
# With shops (78 and 42 taken out)
np.median(sneakers_data[(sneakers_data['shop_id'] != 42) & (sneakers_data['shop_id'] != 78)]['order_amount'])
```

Out[87]:
```
284.0
```

Using our numpy function, or table above, we conclude that our median is $284 which represents the data accurately. (Very similar to our AOV when we took out shops 78 and 42)

## Question 2

a. **How many orders were shipped by Speedy Express in total?**

```
SELECT COUNT(ShipperName) SE_Count
FROM (SELECT *
        FROM [Orders] o
        LEFT JOIN [Shippers] s
        ON s.ShipperID = o.ShipperID
        WHERE ShipperName = 'Speedy Express')
```

**Answer:** There were 54 orders shipped by Speedy Express

b. **What is the last name of the employee with the most orders?**

```
WITH employee_orders AS (SELECT EmployeeID, COUNT(*) NumOrders
                         FROM [Orders]
                         GROUP BY EmployeeID
                         ORDER BY NumOrders DESC)
SELECT LastName, NumOrders
FROM employee_orders eo
LEFT JOIN [Employees] e
ON eo.EmployeeID = e.EmployeeID
WHERE NumOrders = (SELECT MAX(NumOrders)
                   FROM employee_orders)
```

**Answer:** Peacock is the last name of the employee with the most orders (40)

c. **What product was ordered the most by customers in Germany?**

```
WITH orders_countries AS (SELECT o.OrderID, o.CustomerID, c.Country
                          FROM [Orders] o
                          LEFT JOIN [Customers] c
                          ON o.CustomerID = c.CustomerID),
germany AS (SELECT ProductID, Country, SUM(Quantity) TotalQuantity
            FROM [OrderDetails] od
            LEFT JOIN orders_countries oc
            ON od.OrderID = oc.OrderID
            WHERE Country = 'Germany'
            GROUP BY Country, ProductID)
SELECT ProductName, Country, TotalQuantity
FROM germany g
LEFT JOIN [Products] p
ON g.ProductId = p.ProductId
WHERE TotalQuantity = (SELECT MAX(TotalQuantity)
                       FROM germany)
```

**Answer:** Boston Crab Meat was the product ordered the most by customers in Germany (160)

**Note:** This assumes that we sum quantity of product, not number of purchases