Shopify Data Science Challenge by Laura Manolache

In [1]:
```
# Imporning necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

Q1: On 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 $3145.13. Given that we know these shops are selling sneakers, a relatively affordable item, something seems wrong with our analysis.

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

In [2]:
```
# Load the dataset into a dataframe
data = pd.read_csv('data_set.csv')
data.head()
```

Out[2]:

	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 [3]:
```
# Lookin at initial information about the data set
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 7 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   order_id        5000 non-null   int64 
 1   shop_id         5000 non-null   int64 
 2   user_id         5000 non-null   int64 
 3   order_amount    5000 non-null   int64 
 4   total_items     5000 non-null   int64 
 5   payment_method  5000 non-null   object
 6   created_at      5000 non-null   object
dtypes: int64(5), object(2)
memory usage: 273.6+ KB
```

In attempt to try to answer question Q1.a, one needs to first look at some (order_amount,order_amount since these are the features involved in the average's calculation formula) features distribution/stats to obtain further leads in our initial analysis.

In [4]:
```
data['order_amount'].describe()
```

Out[4]:
```
count      5000.000000
mean       3145.128000
std       41282.539349
min          90.000000
25%         163.000000
50%         284.000000
75%         390.000000
max      704000.000000
Name: order_amount, dtype: float64
```

In [5]:
```
data['total_items'].describe()
```

Out[5]:
```
count    5000.00000
mean        8.78720
std       116.32032
min         1.00000
25%         1.00000
50%         2.00000
75%         3.00000
max      2000.00000
Name: total_items, dtype: float64
```

Initial findings based on the stats obtained above:

```
- the mean value for order_amount is very high (aprox. 3145.13) when compared to quantiles of the dataset;
- the shoes are bought in bulks (maximum of items in orders is 2000) as well, which of course offsets the mean and standard deviation in the average formulae;
- the maximum order_amount value is extremelly high (704000) when compared to 3rd quantile value (390).
```

Based on the findings above:

```
- the Average Order Value (AOV) was obtained as the mean value of the order_amount for the above dataset;
- given the maximum value in the stat above, one could infer that there might be high-value outliers in the data set which are causing the mean value to be so high.
```

Considering that these shops are selling the same model of affordable sneakers, there could be several potential sources for this discrepancy.

Another potential source of discrepacny - Sneaker price markups: Different shops are selling each pair of sneakers at different prices. There may be certain orders where the price of each pair is significantly higher than other orders.

Next we will investigate the prices that each pair of sneakers is being sold at by shops. To find the price of one pair of sneakers per order, divide the order_amount column by the total_items column using numpy.where.

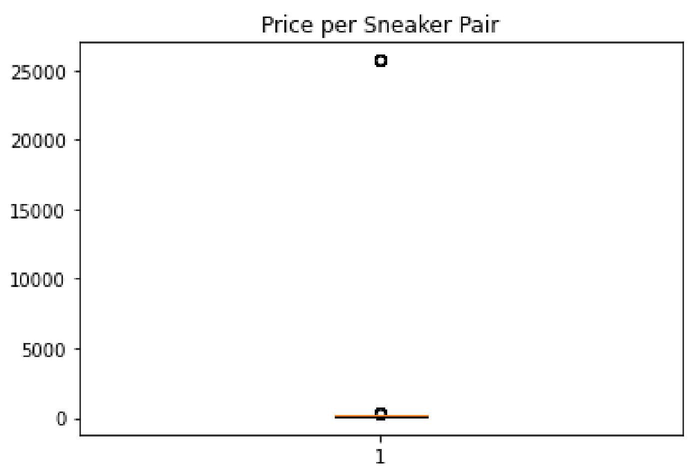
In [6]:
```
# Function that calculates the average price per pair each shops has in the data set
def get_price_per_pair(df):
    df['price/pair'] = np.where(df['total_items'] < 1, df['total_items'], df['order_amount']/df['total_items'])
    return df

df = get_price_per_pair(data)

# Plot the median price value per pair of sneakers in the data set
fig, ax = plt.subplots()
ax.set_title('Price per Sneaker Pair')
ax.boxplot(df['price/pair'])

price_per_pair_median = df['price/pair'].median()
print(price_per_pair_median)
```

```
153.0
```



The maximum average price value per pair is terible high compared to the median average value, which seems like an overpriced pair or an outlier.

In [7]:
```
df.head()
```

Out[7]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at	price/pair
0	1	53	746	224	2	cash	2017-03-13 12:36:56	112.0
1	2	92	925	90	1	cash	2017-03-03 17:38:52	90.0
2	3	44	861	144	1	cash	2017-03-14 4:23:56	144.0
3	4	18	935	156	1	credit_card	2017-03-26 12:43:37	156.0
4	5	18	883	156	1	credit_card	2017-03-01 4:35:11	156.0

In [8]:
```
df[['price/pair']].describe()
```

Out[8]:

	price/pair
count	5000.000000
mean	387.742800
std	2441.963725
min	90.000000
25%	133.000000
50%	153.000000
75%	169.000000
max	25725.000000

Next we will find the maximum median price value per pair and the shop associated with the value.

In [9]:
```
# Group by shop_id, averaging purchases per shop
p1_grouped = df.groupby(df['shop_id'])['price/pair'].mean().reset_index().sort_values(by=['price/pair'], ascending = False)
p1_grouped.head(10)
```

Out[9]:

	shop_id	price/pair
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

In [10]:
```
# Average after removing shop 78 from calculation
round(np.mean(df[df['shop_id'] != 78]['price/pair']), 2)
```

Out[10]: 152.48

152 seems affordable, but the vaue has not changed much after removing outlier(shop 78).

Next looking at 'total_items' column feature.

In [11]:
```
df['total_items'].value_counts()
```

Out[11]:
```
2       1832
1       1830
3        941
4        293
5         77
2000      17
6          9
8          1
Name: total_items, dtype: int64
```

Seems a shop has 17 orders with a bulk of 2000 pairs. Let's find this ship id.

In [12]:
```
df[df['total_items'] == 2000]['shop_id'].unique()
```

Out[12]:
```
array([42], dtype=int64)
```

In [13]:
```
sneakers_p2 = df[['shop_id', 'user_id', 'order_amount', 'total_items']]
```

In [14]:
```
sneakers_p2[sneakers_p2['shop_id'] == 42].head()
```

Out[14]:

	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 [15]:
```
sneakers_p2[sneakers_p2['user_id'] == 607].head()
```

Out[15]:

	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

Seems like the outlieir here is a unique user placing bulk orders to a unique shop. We can elimnate this outlier and recalculate the average.

In [16]:
```
# Average order amount without considerng shop 42 and shop 78.
round(np.mean(df[(df['shop_id'] != 42) & (df['shop_id'] != 78)])['order_amount'], 2)
```

Out[16]: 300.16

In [17]:
```
# Average order items without considerng shop 42 and shop 78.
round(np.mean(df[(df['shop_id'] != 42) & (df['shop_id'] != 78)])['total_items'], 3)
```

Out[17]: 1.996

In [18]:
```
# Average price scaled to 1 item
round(np.mean(df[(df['shop_id'] != 42) & (df['shop_id'] != 78)])['price/pair'], 2)
```

Out[18]: 150.4

This value hasn't changed much. The conclusion is that this measure does not represent this data set correctly, it is skewed.

b. What metric would you report for this dataset?

Considering the previous analysis, we found the average wasn't the best indicator of our analysis. It seems like we weren't considering anomalies in the data set, which can lead to a skewed AOV.

In [19]:
```
# Looking at our order_amount once again
data['order_amount'].describe().to_frame().round(2)
```

Out[19]:

	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

In this case, one can observe that the dataset filtered has a clearer mean and median value.

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.

b. What metric would you report for this dataset?

Based on the findings from question 1a, the median metric seems to be less influenced by the outliers better fitted for a statistical analisys.

c. What is its value?

In [20]:
```
# Median of dataset
np.median(data['order_amount'])
```

Out[20]: 284.0

In [21]:
```
# With shops (78 and 42 taken out)
np.median(data[(data['shop_id'] != 42) & (data['shop_id'] != 78)]['order_amount'])
```

Out[21]: 284.0

QUESTION 2a:

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

There were 54 orders shipped by Speedy Express

QUESTION 2b:

```
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)
```

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

Question 2c

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

Boston Crab Meat was the product ordered the most by customers in Germany (160=count of the product)

In [ ]:

In [ ]:

In [ ]: