In [398]:
```
#import pandas library to be used
import pandas as pd
```

# Fall 2021 Data Science Intern Challenge

## Assumptions:

Data set is as is and does not have any issues: No issues such as formatting, lack of headers and incorrect data types, headers were verified in the excel spreadsheet

All data in the imported set is valid for importation purposes.

All order amount values are in the same currency.

All shop_ids and user_ids have been entered correctly.

NOTE: Some tasks were performed outside of this python script, for information that was easily analysed from the google docs file, using excel formulas and sorting the data such as: Date range verification - all dates are in March of the same year.

Some resources used to solve this problem: https://www.shopify.ca/blog/average-order-value (https://www.shopify.ca/blog/average-order-value) https://www.optimizely.com/optimization-glossary/average-order-value/ (https://www.optimizely.com/optimization-glossary/average-order-value/) https://www.bigcommerce.ca/ecommerce-answers/what-average-order-value/ (https://www.bigcommerce.ca/ecommerce-answers/what-average-order-value/)

```
In [399]: #define the list of the dataset from the google docs file
          data_source = "https://docs.google.com/spreadsheets/d/16i38oonuX1y1g7C_UAm
          iK9GkY7cS-64DfiDMNiR41LM/export?format=csv&gid=0"

          #import data as a csv
          data_set = pd.read_csv(data_source)

          print("This is the data set being used:\n", data_set, "\n")
```

```
This is the data set being used:
       order_id  shop_id  user_id  order_amount  total_items payment_method
\
0            1       53      746           224            2           cash
1            2       92      925            90            1           cash
2            3       44      861           144            1           cash
3            4       18      935           156            1    credit_card
4            5       18      883           156            1    credit_card
...        ...      ...      ...           ...          ...            ...
4995      4996       73      993           330            2          debit
4996      4997       48      789           234            2           cash
4997      4998       56      867           351            3           cash
4998      4999       60      825           354            2    credit_card
4999      5000       44      734           288            2          debit

               created_at
0     2017-03-13 12:36:56
1     2017-03-03 17:38:52
2      2017-03-14 4:23:56
3     2017-03-26 12:43:37
4      2017-03-01 4:35:11
...                   ...
4995  2017-03-30 13:47:17
4996  2017-03-16 20:36:16
4997   2017-03-19 5:42:42
4998  2017-03-16 14:51:18
4999  2017-03-18 15:48:18

[5000 rows x 7 columns]
```

The code above shows that there are 5000 rows of data ant 7 columns, with the correct headers, verifying the data was imported correctly from the google docs file

```
In [400]: #given the somewhat large data set, convert from a dictionary to data fram
          e
          data_set = pd.DataFrame(data_set)
```

```
In [401]: #calculate an integer value for the number of rows (orders) in the data se
          t to be used for future calculations
          num_orders = len(data_set)

          #calculate an integer value for the revenue
          total_rev = sum(data_set.order_amount)
```

```
In [402]: AOV = total_rev / num_orders
          print("\nAOV =", AOV)
```

```
AOV = 3145.128
```

## Analysing the Data

The average order value is verified to have been calculated correctly, with a rounded value of $3145, as in the problem defintion. With this, I can rule out the possibility of any arithmetic issues.

However, it is known that there is an issue with the data (from the problem statement), so first thing to do is ensure the data is valid by analysing the relevant columns. The shop_ids and the user_ids are correct, so is the created_at date

I will now check the following respectively:

1. order_id: To ensure that they are unique
2. price, using order_amount and total_items to calculate the unit price for analysis
3. quantity of items ordered

After this, I will recalculate the AOV and look at other values that can be used to measure the business growth, comparing them to the original data set and the corrected data set

## 1. Validating the order_ids

```
In [403]: #1. Validating that the order_ids are unique
          val_order_id_set = set(data_set.order_id)
          if len(val_order_id_set) != len(data_set.order_id):
              print("\nDuplicates exist\n")
          else: print("\nThere are not duplicates in the order_id\n")
```

```
There are not duplicates in the order_id
```

## 2. Analysing the price

```
In [404]: #2. To analyse the price, I will breakdown the order_amount to unit_price
          #This will tell me the price charged for a single shoe for each order
          #allowing a better understanding of the data set

          unit_price = data_set.order_amount / data_set.total_items
```

```
In [405]: #update the data set to include the unit_cost
          data_set['unit_price'] = unit_price

          #Verify the data set
          print("\nThis is the new data_set with the unit price of a shoe included:
          \n",data_set)
```

```
This is the new data_set with the unit price of a shoe included:
        order_id  shop_id  user_id  order_amount  total_items payment_method
\
0              1       53      746           224            2           cash
1              2       92      925            90            1           cash
2              3       44      861           144            1           cash
3              4       18      935           156            1    credit_card
4              5       18      883           156            1    credit_card
...          ...      ...      ...           ...          ...            ...
4995        4996       73      993           330            2          debit
4996        4997       48      789           234            2           cash
4997        4998       56      867           351            3           cash
4998        4999       60      825           354            2    credit_card
4999        5000       44      734           288            2          debit

               created_at  unit_price
0     2017-03-13 12:36:56       112.0
1     2017-03-03 17:38:52        90.0
2      2017-03-14 4:23:56       144.0
3     2017-03-26 12:43:37       156.0
4      2017-03-01 4:35:11       156.0
...                   ...         ...
4995  2017-03-30 13:47:17       165.0
4996  2017-03-16 20:36:16       117.0
4997   2017-03-19 5:42:42       117.0
4998  2017-03-16 14:51:18       177.0
4999  2017-03-18 15:48:18       144.0

[5000 rows x 8 columns]
```

The data set includes the unit price now.

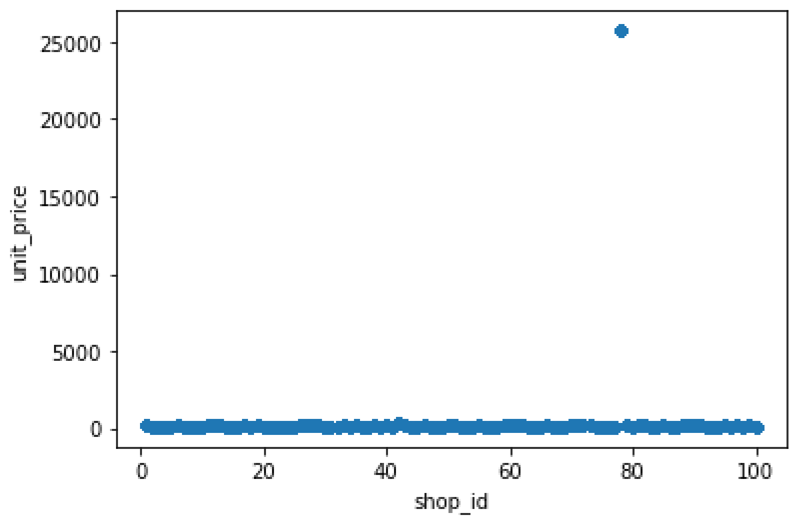
To visualise the data better (instead of going through each row) I will plot the unit_price against shop_id

NOTE: In excel, I sorted by unit price and noticed there was an abnormally high unit price

This plot here is to visualise the data for better understanding

```
In [406]: #Each shop, since selling only one model of shoe charges the same price fo
          r that shoe
          #NOTE: I chose to plot the unit_price against the shop_id because there ar
          e only 100 shops
          #giving me an independent variable with fixed values.

          data_set.plot(x ='shop_id', y='unit_price', kind = 'scatter')
```

```
Out[406]: <AxesSubplot:xlabel='shop_id', ylabel='unit_price'>
```



From this plot, we can see that there is a single major outlier in the data set, where the price is about 25000 per unit (for a shoe).

I will now filter for the shop_ids that have the unit price >20000 (using the data from the plot) and group them by unit_price and shop_id

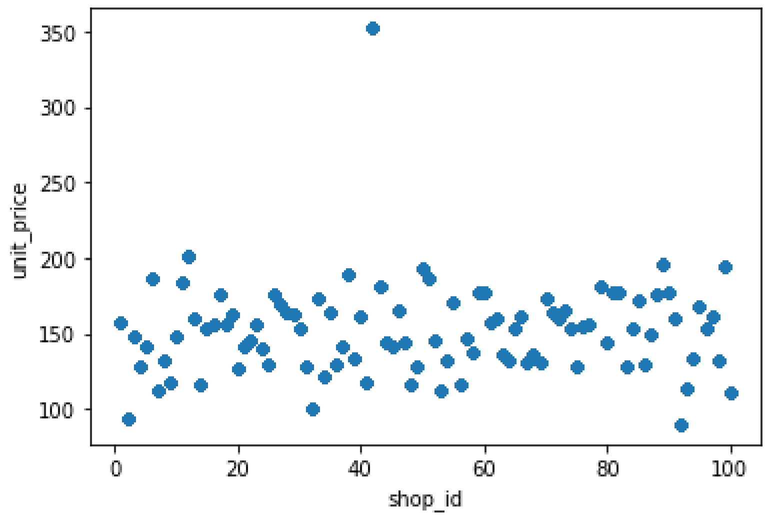
```
In [407]: unit_price_large = data_set.loc[data_set.unit_price > 20000]

          unit_price_large_grouped = unit_price_large.groupby(["shop_id", "unit_pric
          e"])["shop_id"].count()
          print(unit_price_large_grouped)
```

```
shop_id  unit_price
78       25725.0       46
Name: shop_id, dtype: int64
```

From the data set grouped by unit price and shop id, it shows that the unit_price of 25725 appears to be incorrect or a unique outlier This also corellates with the shop ID 78 only, showing that only this shop has the issue in the data set, which I will exclude for purposes of accuracy, given how large it is compared to the other values

NOTE: This step assumes that the unit_price of 25725 is either incorrect - from a bug, from incorrect data entry or a unique outlier This high unit value would skew the results towards a higher AOV value, due to the relatively high revenue

```
In [408]: #Correcting the data set to exclude the outlier price.
          data_set_corrected = data_set.loc[data_set.shop_id != 78]
          data_set_corrected.plot(x ='shop_id', y='unit_price', kind = 'scatter')

Out[408]: <AxesSubplot:xlabel='shop_id', ylabel='unit_price'>
```



For further comparison, I will calculate the standaer deviation for the original data set and compare it to the corrected data set.

```
In [409]: print('The original data unit_price has a standard deviation of:',data_set
          .std().unit_price,'\n'*2)
          print('The corrected data unit_price has a standard deviation of:',data_se
          t_corrected.std().unit_price,'\n'*2)

          The original data unit_price has a standard deviation of: 2441.963725368454
          6


          The corrected data unit_price has a standard deviation of: 31.2602175328963
          9
```

The corrected data set now appears more within reason

## 3. Analysing the quantity of shoes ordered

```
In [410]: total_items_grouped = data_set_corrected.groupby(["total_items"])["total_i
tems"].count()
print("\nData set grouped by the total items, counting how many times the
 same quantity of shoes were purchased:\n\n",total_items_grouped)

total_items_grouped = pd.DataFrame(total_items_grouped)
#total_items_grouped = total_items_grouped.rename(columns = {total_items:I
T}, inplace = False)
#print("\nData set grouped by the total items, counting how many times the
same quantity of shoes were purchased:\n\n",total_items_grouped)

#total_items_grouped.plot(x ='total_items', y='[total_items].count()', kin
d = 'scatter')
#print(len(total_items_grouped))
#total_items_groupedplt = data_set.groupby(["total_items"])["total_item
s"].plot(kind = 'scatter')
```

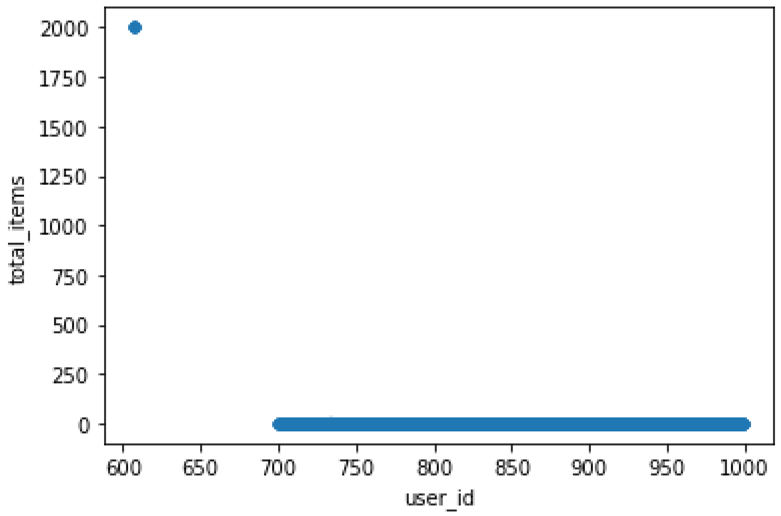
```
Data set grouped by the total items, counting how many times the same quant
ity of shoes were purchased:

 total_items
1       1811
2       1816
3        932
4        292
5         77
6          8
8          1
2000      17
Name: total_items, dtype: int64
```

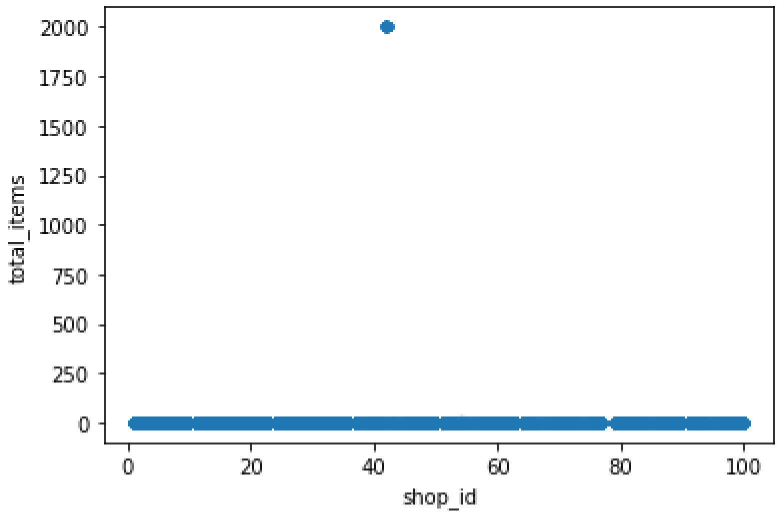
From this data, there appears to be a relatively large quantity of shoes (2000) ordered 17 times, when compared to the other number of orders ranging from 1 - 8, this data is clearly an outlier.

This may be a large retailer that buys a fixed amount of shoes with every purchace. Analysing the date data did not show a trend in the order dates, but showed that they ordered the same quantity each time. I will plot the total_items against the user id and shop id Note: I intuitively chose user_id and shop id here because the users are placing the orders and the shops are fulfilling them. I tested this plot with other values, such as unit_cost and decided the user_id and shop_id showed the data best

```
In [411]: data_set_corrected.plot(x ='user_id', y='total_items', kind = 'scatter')
          data_set_corrected.plot(x ='shop_id', y='total_items', kind = 'scatter')
```

```
Out[411]: <AxesSubplot:xlabel='shop_id', ylabel='total_items'>
```





I will now create a dataset with the data where the total_items ordered is 2000, for further analysis, to see if there is a trend with the user_id or shop_id, or a relationship between both.

```
In [412]: #Dataset with high orders
          total_items_large = data_set_corrected.loc[data_set_corrected.total_items
          == 2000]

          #grouped by user_id only
          total_items_large_groupedu = total_items_large.groupby(["user_id"])["total
          _items"].count()

          #grouped by shop_id only
          total_items_large_groupeds = total_items_large.groupby(["shop_id"])["total
          _items"].count()

          #grouped by both user_id and shop_id
          total_items_large_groupedus = total_items_large.groupby(["user_id", "shop_
          id"])["total_items"].count()

          print(total_items_large_groupedu,'\n')
          print(total_items_large_groupeds,'\n')
          print(total_items_large_groupedus,'\n')
```

```
user_id
607    17
Name: total_items, dtype: int64

shop_id
42    17
Name: total_items, dtype: int64

user_id  shop_id
607      42         17
Name: total_items, dtype: int64
```

Inspecting the data further in excel, looking at the total_items column, one thing to notice is the large total_items ordered come from a single shop ID 42, and user ID 607,

Given that all these orders were from a single store, it could be that these orders were made by a customer that regularly buys the same amount of shoes wholesale as previously mentioned

It is important to note that this shop sold at other quantities to other customers, and only user 607 ordered such a large amount each time.

Thus using this customer to calculate the AOV or other groth tracking values (such as the modal value) will skew the data higher As such, I have decided to also exclude it from the data set.

I will now filter for where the total_items ordered is 2000 exclude this data, which is also where user_id is 607

```
In [413]: data_set_corrected2 = data_set_corrected.loc[data_set_corrected.user_id !=
          607]
          print(data_set_corrected2)
```

```
      order_id  shop_id  user_id  order_amount  total_items payment_method  \
0            1       53      746           224            2           cash
1            2       92      925            90            1           cash
2            3       44      861           144            1           cash
3            4       18      935           156            1    credit_card
4            5       18      883           156            1    credit_card
...        ...      ...      ...           ...          ...            ...
4995      4996       73      993           330            2          debit
4996      4997       48      789           234            2           cash
4997      4998       56      867           351            3           cash
4998      4999       60      825           354            2    credit_card
4999      5000       44      734           288            2          debit

               created_at  unit_price
0     2017-03-13 12:36:56       112.0
1     2017-03-03 17:38:52        90.0
2      2017-03-14 4:23:56       144.0
3     2017-03-26 12:43:37       156.0
4      2017-03-01 4:35:11       156.0
...                   ...         ...
4995  2017-03-30 13:47:17       165.0
4996  2017-03-16 20:36:16       117.0
4997   2017-03-19 5:42:42       117.0
4998  2017-03-16 14:51:18       177.0
4999  2017-03-18 15:48:18       144.0

[4937 rows x 8 columns]
```

I will now compare the standard deviation of the total_items from the previous data set to this data set

```
In [414]: print('In the previous data set (data_set_corrected) total_items has a sta
          ndard deviation of:',data_set_corrected.std().total_items,'\n'*2)
          print('In the corrected data set (data_set_corrected2) total_items has a s
          tandard deviation of:',data_set_corrected2.std().total_items,'\n'*2)
```

```
In the previous data set (data_set_corrected) total_items has a standard de
viation of: 116.85728599309454


In the corrected data set (data_set_corrected2) total_items has a standard
deviation of: 0.9828207382187315
```

The standard deviation is much less after the data is corrected, this shows the closeness in values of the total items after the large total items has been excluded

## The AOV can now be calculated with this "incorrrect" data excluded

In [415]:
```
#recalculate the AOV
AOV_corrected2 = (sum(data_set_corrected2.iloc[:,3])) / len(data_set_corre
cted2)

print("""\nThe new AOV after the data has been cleaned up is:\n""", AOV_co
rrected2)
```

```
The new AOV after the data has been cleaned up is:
 302.58051448247926
```

# In summary, the issue with the data set appears to be abnormally high unit costs from a single shop, as well as abnormally high orders from a single customer.

## Supplimental analysis

Below, is some analysis of the data sets at different levels show how the relationship between data changes as the data is cleaned up, using the mean, median and mode.

In [416]:
```
mean_data_set = data_set.mean(axis = 0)
median_data_set = data_set.median()
mode_data_set = data_set.mode()

print("From the original data set:\n")
print(f"""The mean of the order amount and total item columns respectivel
y:
Mean order amount:\n{mean_data_set.order_amount}
\nMean total items ordered:\n{mean_data_set.total_items}\n""")

print(f"""\nThe median of the order amount and total item columns respecti
vely:
\nMedian order amount:\n{median_data_set.order_amount}
\nMedian total items ordered:\n{median_data_set.total_items}\n""")

print(f"""\nThe mode of the order amount and total item columns respective
ly:
Mode order amount:\n{mode_data_set.order_amount[0]}
\nMode total items ordered:\n{mode_data_set.total_items[0]}\n""")

print('='*30,'\n'*2)

mean_data_set_corrected = data_set_corrected.mean(axis = 0)
median_data_set_corrected = data_set_corrected.median(axis = 0)
mode_data_set_corrected = data_set_corrected.mode(axis = 0)

print("From the inital data correction, excluding only the high priced sho
es of 25725\n")
print(f"""\nThe mean of the order amount and total item columns respective
ly:
Mean order amount:\n{mean_data_set_corrected.order_amount}
\nMean total items ordered:\n{mean_data_set_corrected.total_items}\n""")

print(f"""\nThe median of the order amount and total item columns respecti
vely:
\nMedian order amount:\n{median_data_set_corrected.order_amount}
\nMedian total items ordered:\n{median_data_set_corrected.total_items}\n
""")

print(f"""\nThe mode of the order amount and total item columns respective
ly:
Mode order amount:\n{mode_data_set_corrected.order_amount[0]}
\nMode total items ordered:\n{mode_data_set_corrected.total_items[0]}\n"""
)

print('='*30,'\n'*2)
mean_data_set_corrected2 = data_set_corrected2.mean(axis = 0)
median_data_set_corrected2 = data_set_corrected2.median(axis = 0)
mode_data_set_corrected2 = data_set_corrected2.mode()

print("From the final data correction, excluding the high unit price of 25
725, and high number items orderd, 2000:\n")

print(f"""\nThe mean of the order amount and total item columns respective
ly:
Mean order amount:\n{mean_data_set_corrected2.order_amount}
\nMean total items ordered:\n{mean_data_set_corrected2.total_items}\n""")

print(f"""\nThe median of the order amount and total item columns respecti
vely:
\nMedian order amount:\n{median_data_set_corrected2.order_amount}
\nMedian total items ordered:\n{median_data_set_corrected2.total_items}\n
""")

print(f"""\nThe mode of the order amount and total item columns respective
ly:
Mode order amount:\n{mode_data_set_corrected2.order_amount[0]}
\nMode total items ordered:\n{mode_data_set_corrected2.total_items[0]}\n
""")
```

```
From the original data set:

The mean of the order amount and total item columns respectively:
Mean order amount:
3145.128

Mean total items ordered:
8.7872


The median of the order amount and total item columns respectively:

Median order amount:
284.0

Median total items ordered:
2.0


The mode of the order amount and total item columns respectively:
Mode order amount:
153.0

Mode total items ordered:
2.0

==============================


From the inital data correction, excluding only the high priced shoes of 25
725


The mean of the order amount and total item columns respectively:
Mean order amount:
2717.3677836092047

Mean total items ordered:
8.851029471134437


The median of the order amount and total item columns respectively:

Median order amount:
284.0

Median total items ordered:
2.0


The mode of the order amount and total item columns respectively:
Mode order amount:
153.0

Mode total items ordered:
2.0

==============================
From the final data correction, excluding the high unit price of 25725, and
high number items orderd, 2000:


The mean of the order amount and total item columns respectively:
Mean order amount:
302.58051448247926

Mean total items ordered:
1.9947336439133077


The median of the order amount and total item columns respectively:

Median order amount:
284.0

Median total items ordered:
2.0


The mode of the order amount and total item columns respectively:
Mode order amount:
153.0

Mode total items ordered:
2.0
```

From the values above, the Mode and Median values remained the same regardless of the data set.

This is because the outliers were much less than the total data set, as such did not affect the mode and median

On the other hand, due to the way Mean is calculated, there is a vast difference in all 3 values

For this data set, using the median or mode, without correcting the data will give fairly accurate results, while the mean would not.