Summer_2021_DS_Internship_Challenge_Shopify_Question_1

January 17, 2021

1 Problem Statement

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.

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 dataset?
3. What is its value?

2 Summary of The Answers

By investigating the dataset, I found that some enormous order amount values caused the abnormal AOV. These values come from two different sources:

- A huge unit price of sneakers ($25725) in shop No. 78
- A very large number of items ordered (2000 items in each order) in shop No. 42

Even though these values are very different from most of the data, they did occur periodically over time. Therefore, after careful consideration, I decided not simply to drop the rows with large order_amount values. **Instead, I used the median order value (MOV) as the metric. The MOV value is $284.0, which is more reasonable to describe the dataset and more helpful for the analysis.**

In addition, I would recommend checking the data acquisition process for shop No.78, which has all its sneaker at an abnormal price of $25725. I would also check the orders placed in shop No. 42, as some orders were placed simultaneously down to second, and have the possibility of being counted repeatedly.

I provide my detailed analysis below to support my conclusions:

3 Overview of the Dataset

First, let's get an overall picture of the dataset:

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[2]:
```
pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
```

[3]:
```
# Read csv file
df_raw = pd.read_csv(r"C:\DataScience\Jupyter Files\Internship␣
↪Applications\Shopify Winter 2021\2019 Winter Data Science Intern Challenge␣
↪Data Set - Sheet1.csv")
```

[4]:
```
df_raw.head(20)
```

[4]:
```
    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
5          6       58      882           138            1    credit_card
6          7       87      915           149            1           cash
7          8       22      761           292            2           cash
8          9       64      914           266            2          debit
9         10       52      788           146            1    credit_card
10        11       66      848           322            2    credit_card
11        12       40      983           322            2          debit
12        13       54      799           266            2    credit_card
13        14      100      709           111            1           cash
14        15       87      849           447            3    credit_card
15        16       42      607        704000         2000    credit_card
16        17       17      731           176            1           cash
17        18       28      752           164            1    credit_card
18        19       83      761           258            2           cash
19        20       63      898           408            3    credit_card

             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
5   2017-03-14 15:25:01
6   2017-03-01 21:37:57
7    2017-03-08 2:05:38
```

```
8   2017-03-17 20:56:50
9   2017-03-30 21:08:26
10  2017-03-26 23:36:40
11  2017-03-12 17:58:30
12  2017-03-16 14:15:34
13   2017-03-22 2:39:49
14  2017-03-10 11:23:18
15   2017-03-07 4:00:00
16   2017-03-21 4:23:38
17  2017-03-21 12:09:07
18  2017-03-17 13:18:47
19  2017-03-29 15:11:52
```

As described in a shopify blog, “average order value (AOV) is the average amount of money each customer spends per transaction with your store. You can calculate your average order value using this simple formula: **Total revenue / number of orders = average order value**”.

After a quick view on the dataset, the features directly relevent for calculating AOV are:

- order_id: this feature describes the individual order ID. Ideally, every order should generate a distinct order ID. Total number of orders can thus be found by calculating the total number of order IDs.
- order_amount: this feature describes the value of each order. Total revenue can be found by sum up all the values in this column.

Based on the data, we can calculate the naive AOV stated in the problem.

[5]:
```
aov_naive = sum(df_raw['order_amount']) / len(df_raw['order_id'])
print("Naive AOV: ${0:.2f}".format(aov_naive))
```

```
Naive AOV: $3145.13
```

Based on the definitions, the calculation process of the above AOV seems correct. However, **the problem is that an AOV of $3145.13 seems to be too big for sneaker shops**. So we need to find out the plausible causes. I start by looking at the overall statistics of the dataset:

[6]:
```
df_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 7 columns):
order_id          5000 non-null int64
shop_id           5000 non-null int64
user_id           5000 non-null int64
order_amount      5000 non-null int64
total_items       5000 non-null int64
payment_method    5000 non-null object
created_at        5000 non-null object
dtypes: int64(5), object(2)
```

```
memory usage: 273.6+ KB
```

[7]:
```python
df_raw.nunique()
```

[7]:
```
order_id          5000
shop_id            100
user_id            301
order_amount       258
total_items          8
payment_method       3
created_at        4991
dtype: int64
```

[8]:
```python
df_raw.describe()
```

[8]:

	order_id	shop_id	user_id	order_amount	total_items
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.00000
mean	2500.500000	50.078800	849.092400	3145.128000	8.78720
std	1443.520003	29.006118	87.798982	41282.539349	116.32032
min	1.000000	1.000000	607.000000	90.000000	1.00000
25%	1250.750000	24.000000	775.000000	163.000000	1.00000
50%	2500.500000	50.000000	849.000000	284.000000	2.00000
75%	3750.250000	75.000000	925.000000	390.000000	3.00000
max	5000.000000	100.000000	999.000000	704000.000000	2000.00000

From the summary tables above, we can first notice neither Null value nor duplicate value exists in the dataset. **Besides, the data in both the *order_amount* and the *total_items* is severely skewed.** The 75% percentiles are significantly smaller than the maximum values in both columns. This is very likely the reason that caused an abnormal AOV, as averages are sensitive to outliers.

Another interesting finding is that there are only 4991 unique values for *created_at* column. This column indicates the time to second when the purchase was made. This means that some orders were placed at precisely the same time. It is possible, but not very likely that different orders are placed right at the same time. So this part of data is worth delve into.

[9]:
```python
df_raw.loc[df_raw.duplicated(subset=['created_at'], keep=False)].
↪sort_values(by=['created_at'])
```

[9]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method \
520	521	42	607	704000	2000	credit_card
4646	4647	42	607	704000	2000	credit_card
4567	4568	72	740	160	1	debit
726	727	81	883	177	1	cash
15	16	42	607	704000	2000	credit_card
2297	2298	42	607	704000	2000	credit_card
611	612	86	838	130	1	debit
1243	1244	94	920	134	1	cash
1367	1368	42	926	1408	4	cash

1756	1757	27	808	169	1	cash
1104	1105	42	607	704000	2000	credit_card
3332	3333	42	607	704000	2000	credit_card
2835	2836	42	607	704000	2000	credit_card
2969	2970	42	607	704000	2000	credit_card
4056	4057	42	607	704000	2000	credit_card
3617	3618	28	702	164	1	credit_card
4898	4899	91	726	160	1	credit_card

	created_at
520	2017-03-02 4:00:00
4646	2017-03-02 4:00:00
4567	2017-03-07 15:30:37
726	2017-03-07 15:30:37
15	2017-03-07 4:00:00
2297	2017-03-07 4:00:00
611	2017-03-09 10:46:09
1243	2017-03-09 10:46:09
1367	2017-03-13 2:38:34
1756	2017-03-13 2:38:34
1104	2017-03-24 4:00:00
3332	2017-03-24 4:00:00
2835	2017-03-28 4:00:00
2969	2017-03-28 4:00:00
4056	2017-03-28 4:00:00
3617	2017-03-29 7:10:18
4898	2017-03-29 7:10:18

As shown in the table above, half of the orders that were placed simultaneously came from different shops and users. They are orders 4647 and 4568, orders 612 and 1244, orders 1368 and 1757, orders 3617 and 4898. These orders are expected as it is possible that different users coincidentally purchased different items at the same time.

The rest of the orders came from the same shop (shop 42) and the same user (user 607). **These are unusual to me because these orders that happened at the same time could be combined into one single order**. I can think of two reasons: 1. The order amount or the total items for these orders exceeded the maximum value that could be entered into the system. So the system automatically split the orders into smaller portions. 2. These were technical issues regarding these orders, and the orders were somehow repeatedly recorded. To identify which reason was true, extra information would be required. For example, I need to know if the system has maximum limits for the values of order amount/total items. If not, it is worth acquiring more information from the shop or the user to ensure that technical issues did not cause the duplicated records.

4 Exploratory Data Analysis

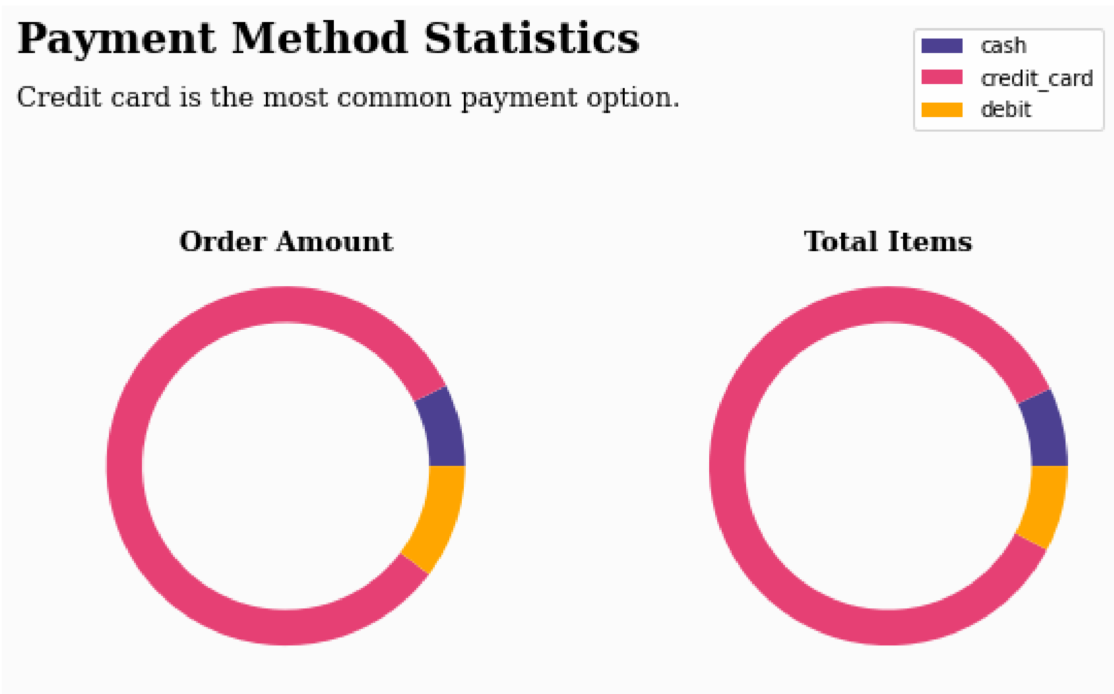
Based on the overview, we found that a possible reason that caused an abnormal AOV was the significantly right-skewed data in *order_amount* and *total_items* columns. However, before naively consider the unusually large values as outliers and remove them, I would like to understand the following questions: 1. Do the unusually large values occur only in one payment method? 2. Do the unusually large values occur only in a specific period?

If the unusually large values only occur at a specific time with a particular payment method, something was likely going wrong at that time. However, if the unusually large values occur periodically in different payment methods, they are probably just regular large orders.

[10]:
```
df_payment_method = df_raw.iloc[:, 3:6]
df_payment_method_sum = df_payment_method.groupby(['payment_method'],␣
 ↪as_index=False).sum()
df_payment_method_size = df_payment_method.groupby(['payment_method']).size().
 ↪reset_index(name='order_counts')
df_payment_method_stat = pd.merge(df_payment_method_sum,␣
 ↪df_payment_method_size, on='payment_method')
df_payment_method_stat['average_item_value'] =␣
 ↪df_payment_method_stat['order_amount'] /␣
 ↪df_payment_method_stat['total_items']
df_payment_method_stat['average_order_value'] =␣
 ↪df_payment_method_stat['order_amount'] /␣
 ↪df_payment_method_stat['order_counts']
```

[11]:
```
# Setting up figure and axes
fig = plt.figure(figsize=(10,4)) # create figure
gs = fig.add_gridspec(ncols=2, nrows=1)
gs.update(wspace=0.1, hspace=0)
ax0 = fig.add_subplot(gs[0, 0])
ax1 = fig.add_subplot(gs[0, 1]) # create axes

# Change background color
background_color = "#fbfbfb"
fig.patch.set_facecolor(background_color) # figure background color
ax0.set_facecolor(background_color) # axes background color
ax1.set_facecolor(background_color) # axes background color

color_map = ["#4c4091", "#e64074", "#ffa600"]

# Order Amount
ax0.pie(x=df_payment_method_stat['order_amount'], colors=color_map,␣
 ↪wedgeprops=dict(width=0.2))

ax0.text(-1.5, 2.3, 'Payment Method Statistics', fontsize=20,␣
 ↪fontweight='bold', fontfamily='serif')
ax0.text(-1.5, 2, 'Credit card is the most common payment option.',
         fontsize=13, fontweight='light', fontfamily='serif')

ax0.text(0, 1.2, 'Order Amount', fontsize=13, fontweight='bold',␣
 ↪fontfamily='serif', horizontalalignment='center')
```

```
# Total Items
ax1.pie(x=df_payment_method_stat['total_items'], colors=color_map,␣
↪wedgeprops=dict(width=0.2))
ax1.text(0, 1.2, 'Total Items', fontsize=13, fontweight='bold',␣
↪fontfamily='serif', horizontalalignment='center')

ax1.legend(df_payment_method_stat["payment_method"], loc="upper right",␣
↪bbox_to_anchor=(1, 1.5))
plt.show()
```

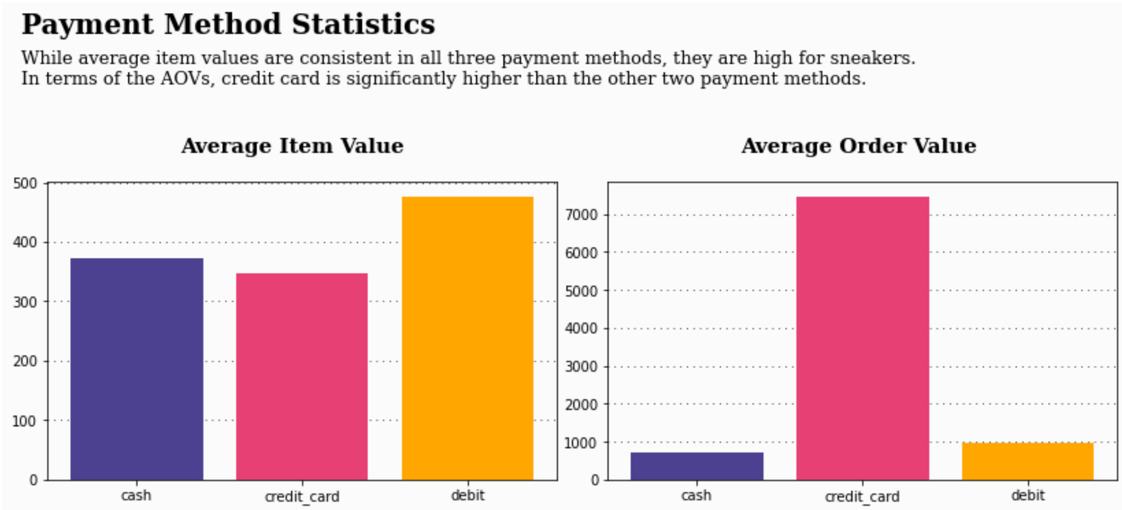


From the above figure, we can tell that credit card is the most used payment method. The distributions based on payment methods in the order amount and total items are aligned.

[12]:
```
# Setting up figure and axes
fig = plt.figure(figsize=(14,4)) # create figure
gs = fig.add_gridspec(ncols=2, nrows=1)
gs.update(wspace=0.1, hspace=0)
ax0 = fig.add_subplot(gs[0, 0])
ax1 = fig.add_subplot(gs[0, 1]) # create axes

# Change background color
background_color = "#fbfbfb"
```

```
fig.patch.set_facecolor(background_color) # figure background color
ax0.set_facecolor(background_color) # axes background color
ax1.set_facecolor(background_color) # axes background color

color_map = ["#4c4091", "#e64074", "#ffa600"]

# Average Item Value
ax0.grid(color='black', linestyle=':', axis='y', zorder=0,  dashes=(1,5))
ax0.bar(df_payment_method_stat["payment_method"],
        df_payment_method_stat['average_item_value'],
        color=color_map, zorder=3
        )
ax0.text(-0.05, 1.5, 'Payment Method Statistics',
         fontsize=20,
         fontweight='bold',
         fontfamily='serif',
         transform=ax0.transAxes
        )
ax0.text(-0.05, 1.33, 'While average item values are consistent in all three␣
 ↪payment methods, ' \
                     'they are high for sneakers. \n' \
                     'In terms of the AOVs, credit card is significantly higher␣
 ↪than ' \
                     'the other two payment methods. ',
         fontsize=13, fontweight='light', fontfamily='serif', transform=ax0.
 ↪transAxes)
ax0.text(0.26, 1.1,
         'Average Item Value',
         fontsize=15,
         fontweight='bold',
         fontfamily='serif',
         transform=ax0.transAxes
        )
# Average Order Value
ax1.grid(color='black', linestyle=':', axis='y', zorder=0,  dashes=(1,5))
ax1.bar(df_payment_method_stat["payment_method"],
        df_payment_method_stat['average_order_value'],
        color=color_map, zorder=3
       )

ax1.text(0.26, 1.1,
         'Average Order Value',
         fontsize=15,
         fontweight='bold',
         fontfamily='serif',
         transform=ax1.transAxes
        )
```

```
plt.show()
```



The average item values for sneakers are higher than my expectation. In my opinion, I would consider a pair of sneakers worth over $300 as "expensive". This data may deviate from the general impressions for the price of a sneaker.

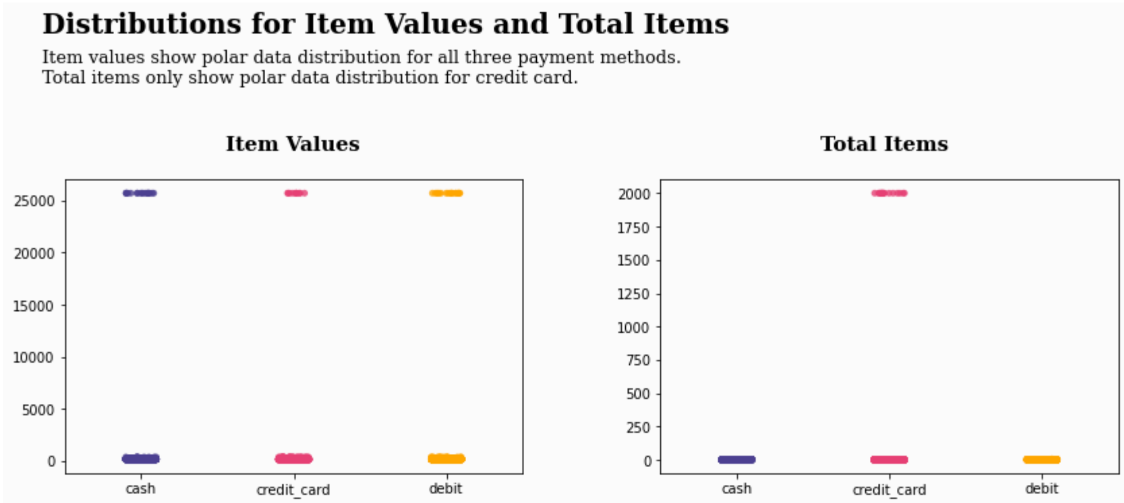
We also notice that **the average order value for credit cards is significantly higher than the other two payment methods**. Considering that the average item value for credit cards is only about $340, this means that the average number of items per order is much higher for credit cards.

Let's take a closer look to see the distributions for the item value and items per order.

[13]:
```
df_raw['item_values'] = df_raw['order_amount'] / df_raw['total_items']
df_cash = df_raw[df_raw['payment_method']=='cash']
df_credit = df_raw[df_raw['payment_method']=='credit_card']
df_debit = df_raw[df_raw['payment_method']=='debit']
```

[14]:
```
# Setting up figure and axes
fig = plt.figure(figsize=(14,4)) # create figure
gs = fig.add_gridspec(ncols=2, nrows=1)
gs.update(wspace=0.3, hspace=0)
ax0 = fig.add_subplot(gs[0, 0])
ax1 = fig.add_subplot(gs[0, 1]) # create axes

# Change background color
background_color = "#fbfbfb"
fig.patch.set_facecolor(background_color) # figure background color
ax0.set_facecolor(background_color) # axes background color
ax1.set_facecolor(background_color) # axes background color
```

```
sns.set_palette(sns.color_palette(color_map))

sns.stripplot(ax=ax0, x='payment_method', y='item_values', data=df_raw,
              marker='o', jitter=True, alpha=0.8)
ax0.set(xlabel=None)
ax0.set(ylabel=None)
ax0.text(-0.05, 1.5, 'Distributions for Item Values and Total Items',
         fontsize=20,
         fontweight='bold',
         fontfamily='serif',
         transform=ax0.transAxes
        )
ax0.text(-0.05, 1.33, 'Item values show polar data distribution for all three␣
↪payment ' \
                     'methods. \n' \
                     'Total items only show polar data distribution for credit␣
↪card. ',
         fontsize=13, fontweight='light', fontfamily='serif', transform=ax0.
↪transAxes
        )
ax0.text(0.35, 1.1,
         'Item Values',
         fontsize=15,
         fontweight='bold',
         fontfamily='serif',
         transform=ax0.transAxes
        )

sns.stripplot(ax=ax1, x='payment_method', y='total_items', data=df_raw,␣
↪marker='o',
              jitter=True, alpha=0.8)
ax1.set(xlabel=None)
ax1.set(ylabel=None)
ax1.text(0.35, 1.1,
         'Total Items',
         fontsize=15,
         fontweight='bold',
         fontfamily='serif',
         transform=ax1.transAxes
        )
plt.show()
```



Interestingly, **all payment methods have very polar distributions for item values**, with most of the item values smaller than $1000 and some more than $25000. In terms of total items, as expected, **only credit card has a very polar distribution**, with some total items larger than 2000.

Let's take a close look at these large values in item values and total items.

[15]:
```
df_raw[df_raw['item_values'] > 25000]
```

[15]:
```
      order_id  shop_id  user_id  order_amount  total_items payment_method  \
160        161       78      990         25725            1    credit_card
490        491       78      936         51450            2          debit
493        494       78      983         51450            2           cash
511        512       78      967         51450            2           cash
617        618       78      760         51450            2           cash
691        692       78      878        154350            6          debit
1056      1057       78      800         25725            1          debit
1193      1194       78      944         25725            1          debit
1204      1205       78      970         25725            1    credit_card
1259      1260       78      775         77175            3    credit_card
1384      1385       78      867         25725            1           cash
1419      1420       78      912         25725            1           cash
1452      1453       78      812         25725            1    credit_card
1529      1530       78      810         51450            2           cash
2270      2271       78      855         25725            1    credit_card
2452      2453       78      709         51450            2           cash
2492      2493       78      834        102900            4          debit
2495      2496       78      707         51450            2           cash
2512      2513       78      935         51450            2          debit
2548      2549       78      861         25725            1           cash
2564      2565       78      915         77175            3          debit
```

2690	2691	78	962	77175	3	debit
2773	2774	78	890	25725	1	cash
2818	2819	78	869	51450	2	debit
2821	2822	78	814	51450	2	cash
2906	2907	78	817	77175	3	debit
2922	2923	78	740	25725	1	debit
3085	3086	78	910	25725	1	cash
3101	3102	78	855	51450	2	credit_card
3151	3152	78	745	25725	1	credit_card
3167	3168	78	927	51450	2	cash
3403	3404	78	928	77175	3	debit
3440	3441	78	982	25725	1	debit
3705	3706	78	828	51450	2	credit_card
3724	3725	78	766	77175	3	credit_card
3780	3781	78	889	25725	1	cash
4040	4041	78	852	25725	1	cash
4079	4080	78	946	51450	2	cash
4192	4193	78	787	77175	3	credit_card
4311	4312	78	960	51450	2	debit
4412	4413	78	756	51450	2	debit
4420	4421	78	969	77175	3	debit
4505	4506	78	866	25725	1	debit
4584	4585	78	997	25725	1	cash
4715	4716	78	818	77175	3	debit
4918	4919	78	823	25725	1	cash

	created_at	item_values
160	2017-03-12 5:56:57	25725.0
490	2017-03-26 17:08:19	25725.0
493	2017-03-16 21:39:35	25725.0
511	2017-03-09 7:23:14	25725.0
617	2017-03-18 11:18:42	25725.0
691	2017-03-27 22:51:43	25725.0
1056	2017-03-15 10:16:45	25725.0
1193	2017-03-16 16:38:26	25725.0
1204	2017-03-17 22:32:21	25725.0
1259	2017-03-27 9:27:20	25725.0
1384	2017-03-17 16:38:06	25725.0
1419	2017-03-30 12:23:43	25725.0
1452	2017-03-17 18:09:54	25725.0
1529	2017-03-29 7:12:01	25725.0
2270	2017-03-14 23:58:22	25725.0
2452	2017-03-27 11:04:04	25725.0
2492	2017-03-04 4:37:34	25725.0
2495	2017-03-26 4:38:52	25725.0
2512	2017-03-18 18:57:13	25725.0
2548	2017-03-17 19:36:00	25725.0

```
2564   2017-03-25 1:19:35      25725.0
2690   2017-03-22 7:33:25      25725.0
2773  2017-03-26 10:36:43      25725.0
2818   2017-03-17 6:25:51      25725.0
2821  2017-03-02 17:13:25      25725.0
2906   2017-03-16 3:45:46      25725.0
2922  2017-03-12 20:10:58      25725.0
3085   2017-03-26 1:59:27      25725.0
3101   2017-03-21 5:10:34      25725.0
3151  2017-03-18 13:13:07      25725.0
3167  2017-03-12 12:23:08      25725.0
3403   2017-03-16 9:45:05      25725.0
3440  2017-03-19 19:02:54      25725.0
3705  2017-03-14 20:43:15      25725.0
3724  2017-03-16 14:13:26      25725.0
3780  2017-03-11 21:14:50      25725.0
4040  2017-03-02 14:31:12      25725.0
4079  2017-03-20 21:14:00      25725.0
4192   2017-03-18 9:25:32      25725.0
4311   2017-03-01 3:02:10      25725.0
4412   2017-03-02 4:13:39      25725.0
4420  2017-03-09 15:21:35      25725.0
4505  2017-03-22 22:06:01      25725.0
4584  2017-03-25 21:48:44      25725.0
4715   2017-03-05 5:10:44      25725.0
4918  2017-03-15 13:26:46      25725.0
```

[16]:
```
df_raw[df_raw['total_items'] > 1000]
```

[16]:
```
      order_id  shop_id  user_id  order_amount  total_items payment_method  \
15          16       42      607        704000         2000    credit_card
60          61       42      607        704000         2000    credit_card
520        521       42      607        704000         2000    credit_card
1104      1105       42      607        704000         2000    credit_card
1362      1363       42      607        704000         2000    credit_card
1436      1437       42      607        704000         2000    credit_card
1562      1563       42      607        704000         2000    credit_card
1602      1603       42      607        704000         2000    credit_card
2153      2154       42      607        704000         2000    credit_card
2297      2298       42      607        704000         2000    credit_card
2835      2836       42      607        704000         2000    credit_card
2969      2970       42      607        704000         2000    credit_card
3332      3333       42      607        704000         2000    credit_card
4056      4057       42      607        704000         2000    credit_card
4646      4647       42      607        704000         2000    credit_card
4868      4869       42      607        704000         2000    credit_card
4882      4883       42      607        704000         2000    credit_card
```

```
               created_at  item_values
15     2017-03-07 4:00:00        352.0
60     2017-03-04 4:00:00        352.0
520    2017-03-02 4:00:00        352.0
1104   2017-03-24 4:00:00        352.0
1362   2017-03-15 4:00:00        352.0
1436   2017-03-11 4:00:00        352.0
1562   2017-03-19 4:00:00        352.0
1602   2017-03-17 4:00:00        352.0
2153   2017-03-12 4:00:00        352.0
2297   2017-03-07 4:00:00        352.0
2835   2017-03-28 4:00:00        352.0
2969   2017-03-28 4:00:00        352.0
3332   2017-03-24 4:00:00        352.0
4056   2017-03-28 4:00:00        352.0
4646   2017-03-02 4:00:00        352.0
4868   2017-03-22 4:00:00        352.0
4882   2017-03-25 4:00:00        352.0
```

From the first table, we found that all sneakers with a price above $25000 were sold by shop 78. **To my knowledge, it is implausible to sell sneakers at the cost of $25725.0. Therefore, it is worth verifying if the item sold by shop 78 was truly sneakers.**

According to the second table, all orders with significant total item values happen between the same shop and the same user. Moreover, we've discussed the orders previously from the shop and the user when checking unusual orders that happened simultaneously. Intuitively, I think they might be outliers.

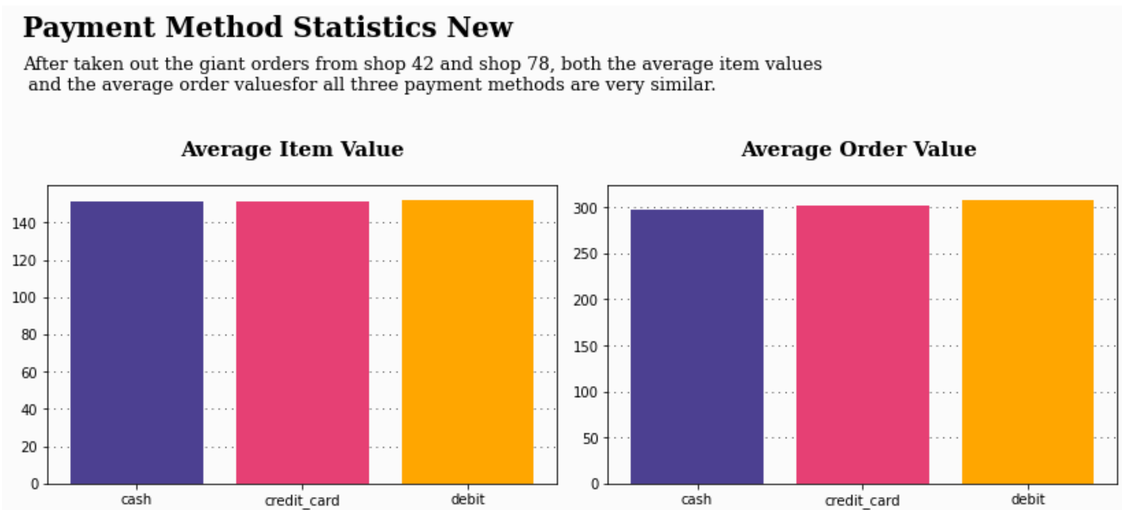
We can verify that the high AOV was indeed caused by the orders with either a very high item price or a huge order quantity:

[17]:
```
df_raw_new = df_raw[(df_raw['total_items']<1000) & (df_raw['item_values'] <␣
 ↪25000)]
df_payment_method_new = df_raw_new.iloc[:, 3:6]
df_payment_method_sum_new = df_payment_method_new.groupby(['payment_method'],␣
 ↪as_index=False).sum()
df_payment_method_size_new = df_payment_method_new.groupby(['payment_method']).
 ↪size().reset_index(name='order_counts')
df_payment_method_stat_new = pd.merge(df_payment_method_sum_new,␣
 ↪df_payment_method_size_new, on='payment_method')
df_payment_method_stat_new['average_item_value'] =␣
 ↪df_payment_method_stat_new['order_amount'] \
                                                    /␣
 ↪df_payment_method_stat_new['total_items']
df_payment_method_stat_new['average_order_value'] =␣
 ↪df_payment_method_stat_new['order_amount'] \
```

```
                                                                    /␣
↪df_payment_method_stat_new['order_counts']
```

[18]:
```
# Setting up figure and axes
fig = plt.figure(figsize=(14,4)) # create figure
gs = fig.add_gridspec(ncols=2, nrows=1)
gs.update(wspace=0.1, hspace=0)
ax0 = fig.add_subplot(gs[0, 0])
ax1 = fig.add_subplot(gs[0, 1]) # create axes

# Change background color
background_color = "#fbfbfb"
fig.patch.set_facecolor(background_color) # figure background color
ax0.set_facecolor(background_color) # axes background color
ax1.set_facecolor(background_color) # axes background color

color_map = ["#4c4091", "#e64074", "#ffa600"]

# Average Item Value
ax0.grid(color='black', linestyle=':', axis='y', zorder=0,  dashes=(1,5))
ax0.bar(df_payment_method_stat_new["payment_method"],
        df_payment_method_stat_new['average_item_value'],
        color=color_map, zorder=3
)
ax0.text(-0.05, 1.5,
         'Payment Method Statistics New',
         fontsize=20,
         fontweight='bold',
         fontfamily='serif',
         transform=ax0.transAxes
        )
ax0.text(-0.05, 1.32,
         'After taken out the giant orders from shop 42 and shop 78, ' \
         'both the average item values \n and the average order values' \
         'for all three payment methods are very similar.',
         fontsize=13, fontweight='light', fontfamily='serif', transform=ax0.
↪transAxes
        )
ax0.text(0.26, 1.1,
         'Average Item Value',
         fontsize=15,
         fontweight='bold',
         fontfamily='serif',
         transform=ax0.transAxes
        )
# Average Order Value
ax1.grid(color='black', linestyle=':', axis='y', zorder=0,  dashes=(1,5))
```

```
ax1.bar(df_payment_method_stat_new["payment_method"],
        df_payment_method_stat_new['average_order_value'],
        color=color_map, zorder=3,
        )

ax1.text(0.26, 1.1,
         'Average Order Value',
         fontsize=15,
         fontweight='bold',
         fontfamily='serif',
         transform=ax1.transAxes
        )
plt.show()
```



After taken out the "outliers", both the average item value and the AOV became very consistent over three payment methods. Also, both values are closer to the public impression.

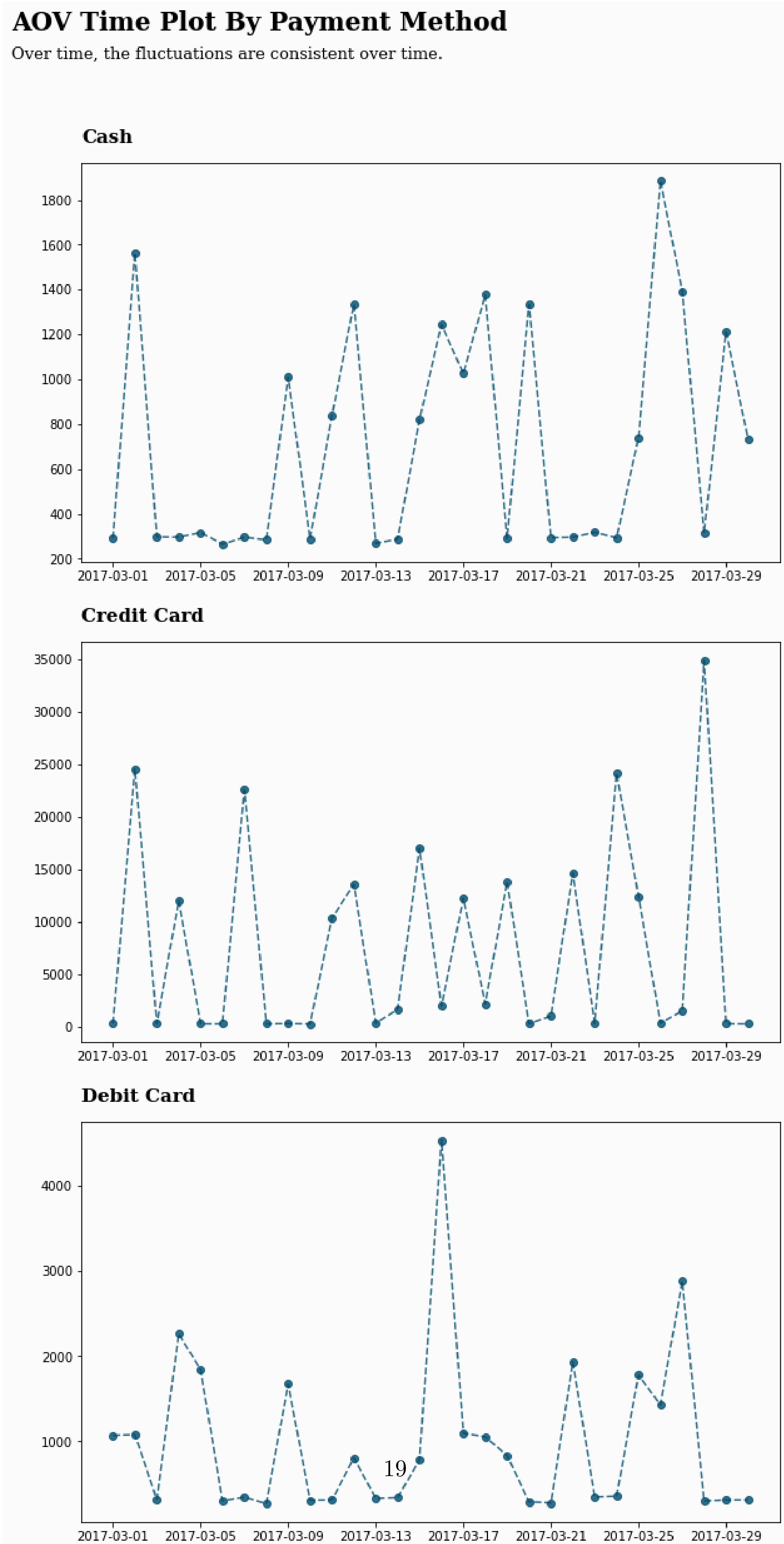
However, if we take a closer look at the *created_at* column for those giant orders, we can notice that the orders were placed quite consistently over time. This means that these orders are probably not "errors". Let's check the AOV over time each day:

[19]:
```
df_time = df_raw.iloc[:, 3:7]
df_time['created_at_date'] = pd.to_datetime(df_time['created_at'].str.split('␣
↪').apply(lambda x: x[0]))
df_time_sum = df_time.groupby(['payment_method', 'created_at_date'],␣
↪as_index=False).sum()
df_time_size = df_time.groupby(['payment_method', 'created_at_date']).size().
↪reset_index(name='order_counts')
df_time_stat = pd.merge(df_time_sum, df_time_size, on=['payment_method',␣
↪'created_at_date'])
```

```
df_time_stat['average_order_value'] = df_time_stat['order_amount'] /␣
↪df_time_stat['order_counts']
df_time_cash = df_time_stat.loc[df_time_stat['payment_method']=='cash'].
↪sort_values(by=['created_at_date'])
df_time_debit = df_time_stat.loc[df_time_stat['payment_method']=='debit'].
↪sort_values(by=['created_at_date'])
df_time_credit = df_time_stat.
↪loc[df_time_stat['payment_method']=='credit_card'].
↪sort_values(by=['created_at_date'])
```

[22]:
```
# Setting up figure and axes
fig = plt.figure(figsize=(10,20)) # create figure
gs = fig.add_gridspec(3, 1)
gs.update(wspace=0.1, hspace=0.2)
ax0 = fig.add_subplot(gs[0, 0])
ax1 = fig.add_subplot(gs[1, 0])
ax2 = fig.add_subplot(gs[2, 0])

# Change background color
background_color = "#fbfbfb"
fig.patch.set_facecolor(background_color) # figure background color
ax0.set_facecolor(background_color) # axes background color
ax1.set_facecolor(background_color) # axes background color
ax2.set_facecolor(background_color) # axes background color

# Cash
ax0.plot(df_time_cash['created_at_date'], df_time_cash["average_order_value"],␣
↪'o--', color="#004c6d", alpha=0.8)
ax0.text(-0.1, 1.33, 'AOV Time Plot By Payment Method', fontsize=20,␣
↪fontweight='bold', fontfamily='serif', transform=ax0.transAxes)
ax0.text(-0.1, 1.26, 'Over time, the fluctuations are consistent over time.',
         fontsize=13, fontweight='light', fontfamily='serif', transform=ax0.
↪transAxes)
ax0.text(0, 1.05,
         'Cash',
         fontsize=15,
         fontweight='bold',
         fontfamily='serif',
         transform=ax0.transAxes
        )

# Credit Card
ax1.plot(df_time_credit['created_at_date'],␣
↪df_time_credit["average_order_value"], 'o--', color="#004c6d", alpha=0.8)

ax1.text(0, 1.05,
```

```
         'Credit Card',
         fontsize=15,
         fontweight='bold',
         fontfamily='serif',
         transform=ax1.transAxes
        )

# Debit Card
ax2.plot(df_time_debit['created_at_date'],␣
 ↪df_time_debit["average_order_value"], 'o--', color="#004c6d", alpha=0.8)
ax2.text(0, 1.05,
         'Debit Card',
         fontsize=15,
         fontweight='bold',
         fontfamily='serif',
         transform=ax2.transAxes
        )

plt.show()
```


AOV Time Plot By Payment Method
Over time, the fluctuations are consistent over time.
Cash
200
400
600
800
1000
1200
1400
1600
1800
2017-03-01
2017-03-05
2017-03-09
2017-03-13
2017-03-17
2017-03-21
2017-03-25
2017-03-29
Credit Card
0
5000
10000
15000
20000
25000
30000
35000
2017-03-01
2017-03-05
2017-03-09
2017-03-13
2017-03-17
2017-03-21
2017-03-25
2017-03-29
Debit Card
1000
2000
3000
4000
2017-03-01
2017-03-05
2017-03-09
2017-03-13
2017-03-17
2017-03-21
2017-03-25
2017-03-29

We see that over time, all three payment methods have relatively consistent fluctuations. Therefore, **it may be inappropriate to remove the massive orders**. Instead, I believe the AOV of \$3145.13 obtained does reflect the true AOV of the orders. However, because of the massive orders that significantly skewed the AOV, this metric might not be beneficial to represent the general order values.

5 A Better Metric

In the problem statement, it did not mention what question we want to answer using the AOV. A reasonable guess is that the team wants to understand a general order value within the month. They may want to compare it with the general order values in different months to analyze customer behavior over time. They may also want to compare it with a specific sneaker shop to see whether this sneaker shop performs better or worse than average so that particular business strategies can be designed for the shop. After all, if the purpose is to understand the general order value of the sneakers, in this case, a **median order value (MOV)** would be more appropriate than the AOV. The MOV is much less sensitive to the outliers and will better represent the center of the data.

The MOV can be found as follow:

[21]:
```
mov = df_raw['order_amount'].median()
print("The median order value is: ${}".format(mov))
```

```
The median order value is: $284.0
```