Shopify Intern Challenge 2021

May 8, 2021

1 Introduction

The high given AOV makes me think there are outliers in the dataset. In this notebook, I check for them, filter them out, and return an adjusted AOV (can also just return the median to take care of outliers). Then I calculate a new metric - the mode - for the dataset. The mode answers the most common purchase price per order, which is a better indicator of the most likely amount someone will spend than the mean.

We'll find that if we want to make decisions such as "Free shipping if you spend at least \$300", it is better to do so with the mode than with the mean. Most customers likely won't spend at least the mean if they see a threshold like \$300, but if the decision is based on a mode of \$150 or \$200, it's more palatable and will push customer who might not spend much on shoes to spend a bit more.

Then I group each customer into deciles by their total order_amount which we can use to target specific customers with campaigns.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

[2]:
```
data = pd.read_csv('2019 Winter Data Science Intern Challenge Data Set - Sheet1.
 ↪csv')
data['created_at'] = pd.to_datetime(data['created_at'])
data.head()
```

[2]:
```
   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

           created_at
0 2017-03-13 12:36:56
1 2017-03-03 17:38:52
2 2017-03-14 04:23:56
3 2017-03-26 12:43:37
```

```
4 2017-03-01 04:35:11
```

[3]:
```
len(data), data.order_id.nunique()
```

[3]:
```
(5000, 5000)
```

[4]:
```
data.dtypes
```

[4]:
```
order_id                   int64
shop_id                    int64
user_id                    int64
order_amount               int64
total_items                int64
payment_method            object
created_at        datetime64[ns]
dtype: object
```

[5]:
```
data.isna().sum()
```

[5]:
```
order_id          0
shop_id           0
user_id           0
order_amount      0
total_items       0
payment_method    0
created_at        0
dtype: int64
```

Verify that AOV is as given ($3145.13) and that the data is over 30 days. Average Order Value = revenue / # of orders

[6]:
```
min(data.created_at), max(data.created_at)
```

[6]:
```
(Timestamp('2017-03-01 00:08:09'), Timestamp('2017-03-30 23:55:35'))
```

[7]:
```
data['order_amount'].sum() / len(data) # naive aov
```

[7]:
```
3145.128
```

1.1 Check for outliers

Quick check for existence of outliers. Note: minimum order amount looks reasonable ($90.00 for shoes sounds fine).

Maximum order amount, $704 000.00, however, looks odd. total_items = 2000 might also be a lot for an individual buyer, but could be a reasonable bulk order from another business. Lets investigate.

[8]:
```
data.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

Ah, so looks like we have a few anomalous entries for user_id=607 and shop_id=42. If it were orders with different user_ids, who have a history of large orders or are well known large businesses, this might not be as suspicious. Also, the frequency and timestamps for these orders is far too frequent for the order value. It's safe to drop these rows and recalculate the average order value, but lets do some more exploration.

[9]:
```
704000/2000 # though on the high side, it's reaching the realm of plausible␣
↪average shoe value.
```

[9]: 352.0

[10]:
```
data[data['order_amount']==704000].sort_values('created_at')
```

[10]:

	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	
60	61	42	607	704000	2000	credit_card	
15	16	42	607	704000	2000	credit_card	
2297	2298	42	607	704000	2000	credit_card	
1436	1437	42	607	704000	2000	credit_card	
2153	2154	42	607	704000	2000	credit_card	
1362	1363	42	607	704000	2000	credit_card	
1602	1603	42	607	704000	2000	credit_card	
1562	1563	42	607	704000	2000	credit_card	
4868	4869	42	607	704000	2000	credit_card	
3332	3333	42	607	704000	2000	credit_card	
1104	1105	42	607	704000	2000	credit_card	
4882	4883	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	

	created_at
520	2017-03-02 04:00:00
4646	2017-03-02 04:00:00

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

[11]:
```
cols = ['order_amount', 'total_items']
Q1 = data[cols].quantile(0.25)
Q3 = data[cols].quantile(0.75)
IQR = Q3 - Q1

data_no_outliers_iqr = data.loc[~((data[cols] < (Q1 - 1.5 * IQR)) |
                             (data[cols] > (Q3 + 1.5 * IQR))).any(axis=1)].
 ↪copy()
data_no_outliers_iqr.describe()
```

[11]:

	order_id	shop_id	user_id	order_amount	total_items
count	4859.000000	4859.000000	4859.000000	4859.000000	4859.000000
mean	2497.395966	49.852645	849.905742	293.715374	1.950196
std	1443.356555	29.049171	86.887496	144.453395	0.919791
min	1.000000	1.000000	700.000000	90.000000	1.000000
25%	1244.500000	24.000000	776.000000	162.000000	1.000000
50%	2498.000000	50.000000	850.000000	280.000000	2.000000
75%	3749.500000	74.000000	925.000000	380.000000	3.000000
max	5000.000000	100.000000	999.000000	730.000000	5.000000

There are a few valid items in terms of order_amount and total_items that are considered outliers by the IQR outlier detection method. Only the one with order_id=692 is a true extreme value due to its order_amount. The others could be plausible orders and we could keep them, but since there are so few, lets drop them along with all the other outliers. They pull up the mean value of orders, but the metric that is more important to business owners is the most frequent value of an order - the mode.

[12]:
```
data[(data['total_items'] < 30) & (data['total_items'] > 5)]
```

[12]:
```
     order_id  shop_id  user_id  order_amount  total_items payment_method  \
691       692       78      878        154350            6          debit
```

```
1563       1564       91      934          960            6         debit
2127       2128       83      745          774            6          cash
2307       2308       61      723          948            6   credit_card
3252       3253       67      706          786            6   credit_card
3538       3539       43      830         1086            6         debit
3865       3866       68      815          816            6         debit
4141       4142       54      733         1064            8         debit
4711       4712       86      883          780            6          cash
4847       4848       13      993          960            6          cash

              created_at
691   2017-03-27 22:51:43
1563  2017-03-23 08:25:49
2127  2017-03-27 06:59:46
2307  2017-03-26 11:29:37
3252  2017-03-29 16:05:41
3538  2017-03-17 19:56:29
3865  2017-03-11 09:31:50
4141  2017-03-07 17:05:18
4711  2017-03-18 14:18:19
4847  2017-03-27 11:00:45
```

1.2 New Metric

The new Average Order Value is \$293.72 (mean of order_amount in `data_no_outliers_iqr`), which is more reasonable. While this is an informative metric, it doesn't complete the picture. Another metric that is useful is the mode, which gives a sense of the most common spending profile.

With no rounding of order_amount, the mode is \$153.00.

Rounding to the nearest 10, the mode is \$160.00. And rounding to the nearest 5, the mode is \$130.00.

So one might set incentives like "Free shipping over $175" or similar.

The median is also calculated as \$280.00, which is close to the mean, so we've cleaned the data from outliers decently well. In fact, the median of order_amount in the original data is \$284.00, so if we didn't want to clean the data we could just answer median is a better metric than the AOV.

[13]:
```python
print('Clean Data Median', data_no_outliers_iqr['order_amount'].median())
print('Original median', data['order_amount'].median())
print('Clean Data Mode', data_no_outliers_iqr['order_amount'].mode().values)
```

```
Clean Data Median 280.0
Original median 284.0
Clean Data Mode [153]
```

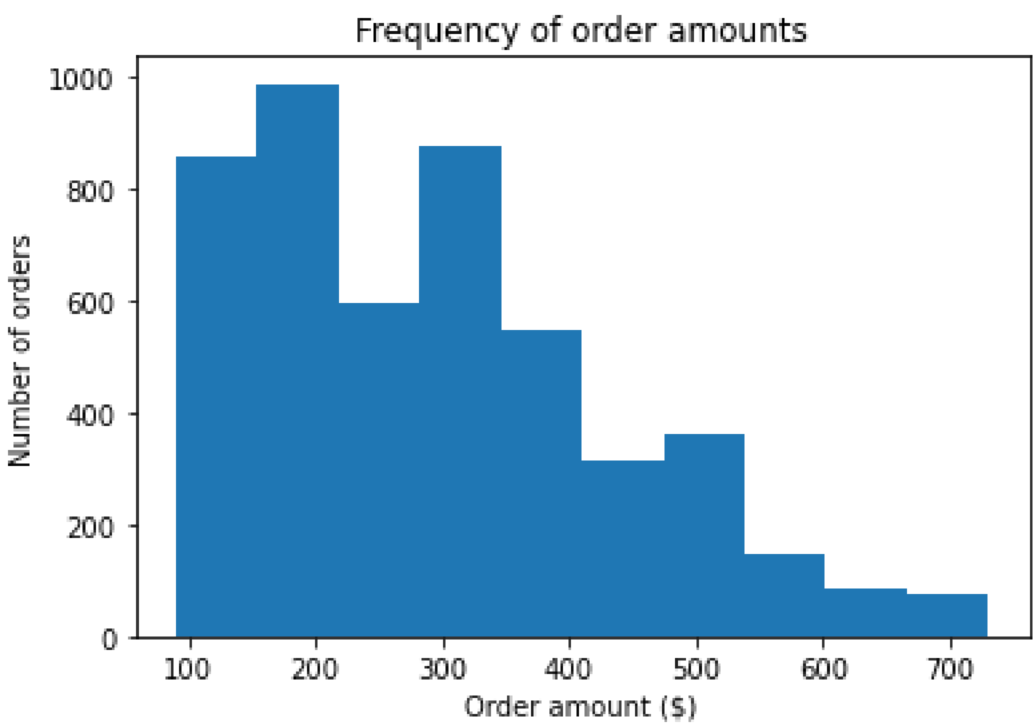
[14]:
```
def round_nearest(value, nearest):
    return int(nearest * round(float(value) / nearest))
```

[15]:
```
def print_metrics(nearest=10):
    data_no_outliers_iqr['rounded_order_amount'] =␣
 ↪data_no_outliers_iqr['order_amount'].apply(lambda x: round_nearest(x,␣
 ↪nearest))
    plt.hist(data_no_outliers_iqr['rounded_order_amount']);
    plt.title('Frequency of order amounts')
    plt.xlabel('Order amount ($)')
    plt.ylabel('Number of orders')
    print('Mode', data_no_outliers_iqr['rounded_order_amount'].mode().values[0])
```

The lowest prices are more common than the highest prices, as expected.

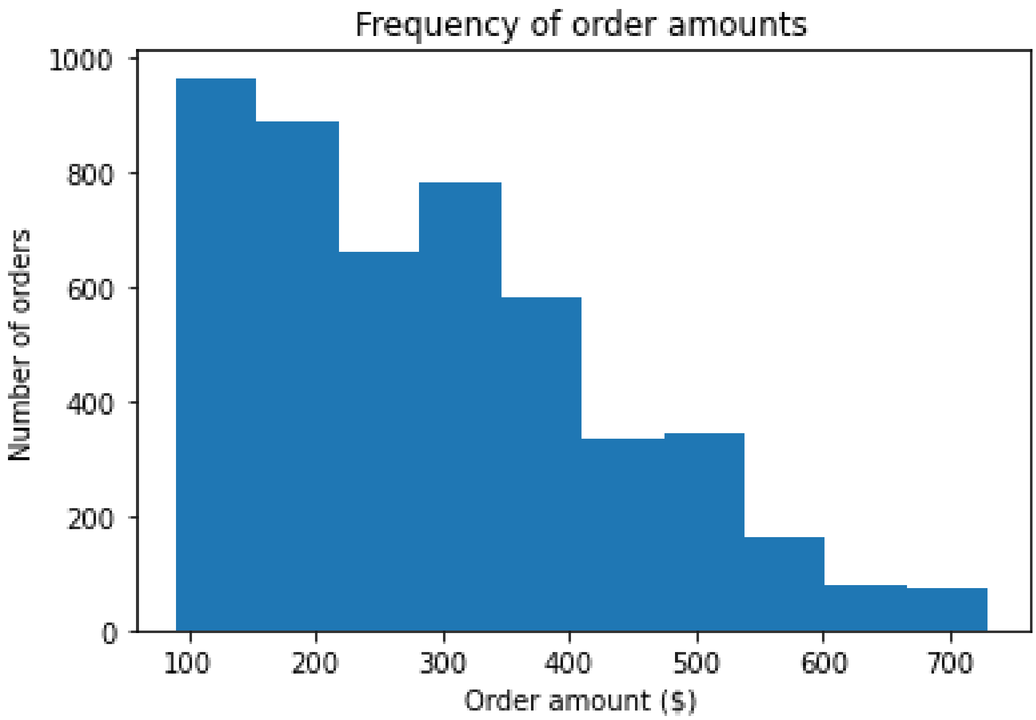
[16]:
```
print_metrics(nearest=5)
```

```
Mode 130
```



[17]:
```
print_metrics(nearest=10)
```

```
Mode 160
```



Mode of order_amount for stores with ID 1 through 100:

[18]:
```
data_no_outliers_iqr.groupby(['shop_id'])['order_amount'].apply(pd.Series.mode).
↪values
```

[18]:
```
array([316,  94, 296, 256, 284, 374, 112, 132, 236, 148, 444, 184, 201,
       320, 116, 306, 156, 176, 156, 163, 127, 284, 292, 312, 280, 130,
       176, 338, 328, 326, 153, 258, 202, 173, 122, 328, 260, 142, 380,
       268, 161, 322, 118, 352, 181, 144, 142, 166, 145, 234, 258, 386,
       187, 292, 224, 266, 171, 342, 117, 294, 138, 178, 177, 316, 160,
       272, 266, 399, 308, 161, 131, 136, 262, 346, 328, 160, 330, 153,
       256, 310, 312, 181, 290, 354, 177, 129, 306, 344, 260, 149, 176,
       196, 356, 160, 180, 114, 402, 336, 153, 162, 133, 195, 111])
```

1.3 Return on Investment / Next Steps

How can we group customers and either prod high paying customers to keep coming back or nurture low paying customers to spend more?

Can also do the grouping for well performing/under performing stores.

[19]:
```
grouped_users = data_no_outliers_iqr.groupby('user_id',␣
↪as_index=False)['order_amount'].sum()
```

```python
# + 1 just to make it jive with talking about the 1st, 2nd, ..., 10th deciles␣
↪rather than 0th
grouped_users['decile'] = pd.qcut(grouped_users.order_amount, q=10,␣
↪labels=False) + 1
grouped_users.head()
```

[19]:

	user_id	order_amount	decile
0	700	4790	6
1	701	5162	7
2	702	4521	5
3	703	6091	9
4	704	3854	3

[20]:
```python
grouped_users.describe()
```

[20]:

	user_id	order_amount	decile
count	300.000000	300.000000	300.00000
mean	849.500000	4757.210000	5.50000
std	86.746758	1299.227102	2.87708
min	700.000000	2102.000000	1.00000
25%	774.750000	3778.750000	3.00000
50%	849.500000	4629.500000	5.50000
75%	924.250000	5541.500000	8.00000
max	999.000000	8952.000000	10.00000

Example of usage: may target these customers of interest

[21]:
```python
def get_user_ids_for_decile(df, decile: int):
    return df[df['decile'] == decile].user_id.values
```

[22]:
```python
get_user_ids_for_decile(grouped_users, 10)
```

[22]:
```
array([705, 718, 734, 736, 739, 745, 756, 759, 768, 778, 785, 786, 787,
       789, 791, 793, 799, 811, 842, 847, 857, 868, 875, 923, 932, 934,
       969, 975, 980, 999])
```

Visualize the deciles

[23]:
```python
aggregated_deciles = grouped_users.groupby('decile',␣
↪as_index=False)['order_amount'].median()
aggregated_deciles
```

[23]:

	decile	order_amount
0	1	2867.0
1	2	3470.5

```
2       3       3775.5
3       4       4135.0
4       5       4496.5
5       6       4737.5
6       7       5086.5
7       8       5545.0
8       9       6222.0
9      10       7086.5
```

[24]:
```
values = aggregated_deciles['order_amount'].values
deciles = aggregated_deciles['decile'].values
print('values', values)
plt.bar(deciles, values);
plt.xticks(deciles)
plt.title('Median value of each decile')
plt.ylabel('Value ($)')
plt.xlabel('Decile');
```

```
values [2867.   3470.5 3775.5 4135.   4496.5 4737.5 5086.5 5545.   6222.   7086.5]
```