Shopify Data Challenge

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Question 1 Given some sample data, write a program to answer the following: click here to access the required data set

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.

Initialize the dataset into a dataframe and check the table details

In [13]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [14]:
```
data = pd.read_excel('Shopify Data Challenge.xlsx')
data.head()
```

Out[14]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
0	1	53	746	224	2	cash	2017-03-13 12:36:56.190
1	2	92	925	90	1	cash	2017-03-03 17:38:51.999
2	3	44	861	144	1	cash	2017-03-14 04:23:55.595
3	4	18	935	156	1	credit_card	2017-03-26 12:43:36.649
4	5	18	883	156	1	credit_card	2017-03-01 04:35:10.773

In [15]:
```
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   datetime64[ns]
dtypes: datetime64[ns](1), int64(5), object(1)
memory usage: 273.6+ KB
```

In [16]:
```
data.describe()['order_amount']
```

Out[16]:
```
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
```

From above statistical result, it is quite clear to see that AOV value **3145.13** comes directly from the total average of order amount. The calculation is correct based on the definition of *AOV*. The mistake must happen with insuffcient data preprocessing

When I first saw the result, I was thinking if there could be some duplicate records that affected the final result. For example, one payment with credit card could fail for some reasons (e.g Insufficient Balance, Card Issues, Payment Interuption) and caused the customer to pay several times. If the failure records were kept in the table, it would definitely change the final result. So the first step is to find the duplicate records then clean them out from raw data.

In [17]:
```
data[data.iloc[:,1:].duplicated(subset = 'created_at', keep = False)].sort_values('created_at')
```

Out[17]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
520	521	42	607	704000	2000	credit_card	2017-03-02 04:00:00
4646	4647	42	607	704000	2000	credit_card	2017-03-02 04:00:00
15	16	42	607	704000	2000	credit_card	2017-03-07 04:00:00
2297	2298	42	607	704000	2000	credit_card	2017-03-07 04:00:00
1104	1105	42	607	704000	2000	credit_card	2017-03-24 04:00:00
3332	3333	42	607	704000	2000	credit_card	2017-03-24 04:00:00
2835	2836	42	607	704000	2000	credit_card	2017-03-28 04:00:00
2969	2970	42	607	704000	2000	credit_card	2017-03-28 04:00:00
4056	4057	42	607	704000	2000	credit_card	2017-03-28 04:00:00

From the above result, we could see duplicate payment happened 4 times. It is quite impossible for a same customer(user_id) to make payment at exactly the same time. I would treat these records as illegal and only keep one of each. **Assume the last payment of each duplicate record is successful**.

In [18]:
```
data.iloc[:,1:].columns
```

Out[18]:
```
Index(['shop_id', 'user_id', 'order_amount', 'total_items', 'payment_method',
       'created_at'],
      dtype='object')
```

In [19]:
```
data.drop_duplicates(subset = ['shop_id', 'user_id', 'order_amount', 'total_items', 'payment_method','created_a
```

Also by reviewing the statistical description from above table, we coud see a very high standard deviation, which means the data is highly skewed. The next step is to find the skewed data and see if they are outliers

In [20]:
```
order_amount_rank = data.groupby(['order_amount']).size().reset_index(name='count').sort_values(by='order_amour
unique_amount_rank = pd.merge(order_amount_rank, data[['order_amount','total_items']], how = 'left', left_on =
unique_amount_rank.drop_duplicates(inplace = True)
unique_amount_rank['single_price'] = unique_amount_rank['order_amount']/unique_amount_rank['total_items']
unique_amount_rank.head(20)
```

Out[20]:

	order_amount	count	total_items	single_price
0	704000	12	2000	352.0
12	154350	1	6	25725.0
13	102900	1	4	25725.0
14	77175	9	3	25725.0
23	51450	16	2	25725.0
39	25725	19	1	25725.0
58	1760	1	5	352.0
59	1408	2	4	352.0
61	1086	1	6	181.0
62	1064	1	8	133.0
63	1056	3	3	352.0
66	980	1	5	196.0
67	965	1	5	193.0
68	960	2	6	160.0
70	948	1	6	158.0
71	935	3	5	187.0
74	920	1	5	184.0
75	890	1	5	178.0
76	885	2	5	177.0
78	880	3	5	176.0

To best find the issues. I picked the top 20 highest order amount from the records and calulated the single price of each sneaker.

It is possible that a supplier may order large amount of sneakers at one time and then sell them to inidividual customers. In this case, records with order amount **704000** could be possible.

For records with other high order amount (> $2,000), we could see the single prices of the sneakers are equally$25.725, which seems too high for a sneaker (even if it is a limited or collection version or luxury brand). These records needs to be further investigated.

In [21]:
```
data.loc[data['order_amount'].isin([51450, 25725, 154350, 102900, 77175, 51450, 25725])].sort_values(by='order_
```

Out[21]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
691	692	78	878	154350	6	debit	2017-03-27 22:51:43.203
2492	2493	78	834	102900	4	debit	2017-03-04 04:37:33.848
1259	1260	78	775	77175	3	credit_card	2017-03-27 09:27:19.843
3724	3725	78	766	77175	3	credit_card	2017-03-16 14:13:25.868
2906	2907	78	817	77175	3	debit	2017-03-16 03:45:46.089
2690	2691	78	962	77175	3	debit	2017-03-22 07:33:25.104
2564	2565	78	915	77175	3	debit	2017-03-25 01:19:35.410
4192	4193	78	787	77175	3	credit_card	2017-03-18 09:25:31.863
4420	4421	78	969	77175	3	debit	2017-03-09 15:21:34.551
3403	3404	78	928	77175	3	debit	2017-03-16 09:45:04.544
4715	4716	78	818	77175	3	debit	2017-03-05 05:10:43.633
617	618	78	760	51450	2	cash	2017-03-18 11:18:41.848
3167	3168	78	927	51450	2	cash	2017-03-12 12:23:07.516
3705	3706	78	828	51450	2	credit_card	2017-03-14 20:43:14.502
3101	3102	78	855	51450	2	credit_card	2017-03-21 05:10:34.147
493	494	78	983	51450	2	cash	2017-03-16 21:39:35.400
511	512	78	967	51450	2	cash	2017-03-09 07:23:13.640
2821	2822	78	814	51450	2	cash	2017-03-02 17:13:25.271
490	491	78	936	51450	2	debit	2017-03-26 17:08:18.911
4412	4413	78	756	51450	2	debit	2017-03-02 04:13:38.530
2818	2819	78	869	51450	2	debit	2017-03-17 06:25:50.921
4079	4080	78	946	51450	2	cash	2017-03-20 21:13:59.919
2512	2513	78	935	51450	2	debit	2017-03-18 18:57:13.421
2495	2496	78	707	51450	2	cash	2017-03-26 04:38:52.497
2452	2453	78	709	51450	2	cash	2017-03-27 11:04:04.363
1529	1530	78	810	51450	2	cash	2017-03-29 07:12:01.466
4311	4312	78	960	51450	2	debit	2017-03-01 03:02:10.223
4040	4041	78	852	25725	1	cash	2017-03-02 14:31:11.566
3440	3441	78	982	25725	1	debit	2017-03-19 19:02:53.732
3780	3781	78	889	25725	1	cash	2017-03-11 21:14:49.542
4584	4585	78	997	25725	1	cash	2017-03-25 21:48:43.570
4505	4506	78	866	25725	1	debit	2017-03-22 22:06:00.804
160	161	78	990	25725	1	credit_card	2017-03-12 05:56:56.834
3151	3152	78	745	25725	1	credit_card	2017-03-18 13:13:07.198
3085	3086	78	910	25725	1	cash	2017-03-26 01:59:26.748
2922	2923	78	740	25725	1	debit	2017-03-12 20:10:58.008
2773	2774	78	890	25725	1	cash	2017-03-26 10:36:43.445
2548	2549	78	861	25725	1	cash	2017-03-17 19:35:59.663
2270	2271	78	855	25725	1	credit_card	2017-03-14 23:58:21.635
1452	1453	78	812	25725	1	credit_card	2017-03-17 18:09:54.089
1419	1420	78	912	25725	1	cash	2017-03-30 12:23:42.551
1384	1385	78	867	25725	1	cash	2017-03-17 16:38:06.279
1204	1205	78	970	25725	1	credit_card	2017-03-17 22:32:21.438
1193	1194	78	944	25725	1	debit	2017-03-16 16:38:25.551
1056	1057	78	800	25725	1	debit	2017-03-15 10:16:44.830
4918	4919	78	823	25725	1	cash	2017-03-15 13:26:46.262

The above result shows the records with sneaker price $25,725 (even cash payment exist with such a high price). All these purchase happened in shop_id 78. In my opinion, either this store is selling some really expensive sneakers or there is a pricing issue. There is also probability that a fraud happens (like the store is doing some money laundrying business). To better figure it out, I suggest we visit this online store and check their products manully.

This case and supplier purchasing could be regarded as special cases. I would not include them to calculate the final result. Next step would be clean these records out from the data.

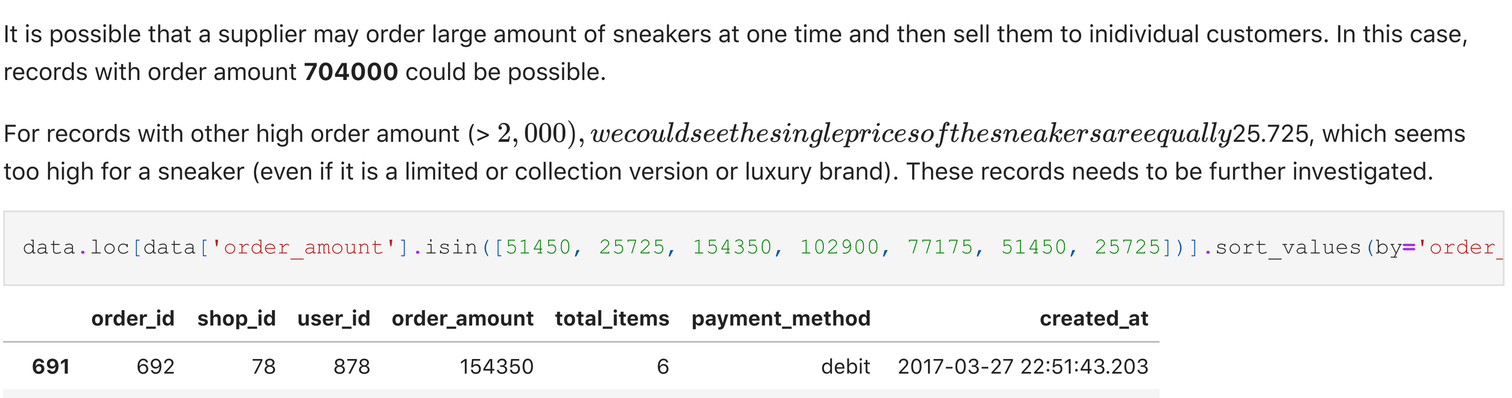
In [22]:
```
processed_result = data.loc[data['order_amount'].isin([704000, 51450, 25725, 154350, 102900, 77175, 51450, 2572
```

In [24]:
```
fig, axes = plt.subplots(1,2, figsize = (30,10))
fig.suptitle('Comparison between processed data and raw data',fontsize = 30)

sns.distplot(data['order_amount'],ax = axes[0])
axes[0].set_title('Order Amount Distribution of Raw Data',fontsize = 20)
axes[0].set_xlabel(xlabel = 'order_amount',fontsize = 20)

sns.distplot(processed_result['order_amount'],ax = axes[1])
axes[1].set_title('Order Amount Distribution of Processed Data',fontsize = 20)
axes[1].set_xlabel(xlabel = 'order_amount',fontsize = 20)
```

Out[24]:
```
Text(0.5, 0, 'order_amount')
```



Even though the processed data is still a little right skewed, but the records here are all reasonable and should all be considered for further analysis

To best evaluate the performance, I would recommend a few more further analysis:

1. Check the records with order_amount $704,000 and see if there are indeed a supplier purchasing. If not, we may need to investigate deeper into those records.
2. Generate another dataset that store all B2B records(e.g. supplier purchasing). Since in this dataset we only have one supplier purchasing(need to be confirmed first) and the records are same, we could skip this one.
3. Check if the records exist a secondary sale(i.e. supplier buy products from another supplier and then sell it to customers)
4. Investigate the store that sell extremely high price products.

b. What metric would you report for this dataset?

Since the processed dataset still has some level of skewness, Mean value will still emphasize some information of the data. Instead of continously using AOV, I would use a more robust metric 'median value' to report for this dataset.

c. What is its value?

In [25]:
```
processed_result.describe()['order_amount']
```

Out[25]:
```
count    4937.000000
mean      302.580514
std       160.804912
min        90.000000
25%       163.000000
50%       284.000000
75%       387.000000
max      1760.000000
Name: order_amount, dtype: float64
```

The median value is $284

Question 2 SQL Challenge

For this question you'll need to use SQL. Follow this link to access the data set required for the challenge. Please use queries to answer the following questions. Paste your queries along with your final numerical answers below.

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

```
SELECT COUNT(DISTINCT O.OrderID) as NumOfShippment
FROM Orders O LEFT JOIN Shippers S
ON O.ShipperID = S.ShipperID
WHERE S.ShipperName = 'Speedy Express'
```

There are **54** orders were shipped by Speedy Express in total

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

```
SELECT E.LastName, COUNT(O.OrderID) AS NumOfOrders
FROM Orders O
LEFT JOIN Employees E
ON O.EmployeeID = E.EmployeeID
GROUP BY E.LastName
ORDER BY 2 DESC
LIMIT 1
```

The last name of the employee with the most orders is **Peacock** with **40** times in total

Sometimes there maybe cases that more than on last names have same number of appearance, which means all of them are the last name with most orders. If we don't identify any rank rules then all these last names should appear in the final result. In this case I would use the following query with **window function**.

```
SELECT LastName, NumOfOrders FROM
(
    SELECT E.LastName,
    COUNT(O.OrderID) AS NumOfOrders,
    dense_rank() over (ORDER BY COUNT(O.OrderID) DESC) AS LastName_rank
    FROM Orders O
    LEFT JOIN Employees E
    ON O.EmployeeID = E.EmployeeID
    GROUP BY 1
) as tmp
WHERE LastName_rank = 1
```

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

```
SELECT
P.ProductName, SUM(OD.Quantity) AS TotalQuantity
FROM Orders O LEFT JOIN Customers C ON O.CustomerID = C.CustomerID
LEFT JOIN OrderDetails OD ON O.OrderID = OD.OrderID
LEFT JOIN Products P ON OD.ProductID = P.ProductID
WHERE C.Country = 'Germany'
GROUP BY 1
ORDER BY 2 DESC
LIMIT 1
```

The product that ordered most by customers in Germany is **Boston Crab Meat** with total quantity of **160**.

Similar to question b, if there are more than one product share the same total quantity, all the productName should appear in the result. In this case, I will use the following query with **window function**

```
SELECT ProductName, TotalQuantity
FROM
(
    SELECT
    P.ProductName, SUM(OD.Quantity) AS TotalQuantity,
    DENSE_RANK() OVER (ORDER BY SUM(OD.Quantity) DESC) AS Quantity_Rank
    FROM Orders O LEFT JOIN Customers C ON O.CustomerID = C.CustomerID
    LEFT JOIN OrderDetails OD ON O.OrderID = OD.OrderID
    LEFT JOIN Products P ON OD.ProductID = P.ProductID
    WHERE C.Country = 'Germany'
    GROUP BY 1
) AS tmp
WHERE Quantity_Rank = 1
```