Shopify Winter '22 Challenge Given: 5,000 orders, 30 day period, 100 shops, each of these shops sells only one model of shoe

Assumption: Every model of shoes must be the same price if sold from the same store

Start by importing useful libraries and reading the data

In [3]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Let's see some stats from this data:

In [9]:

```
df = pd.read_csv('Shopify.csv')
df.describe()
```

Out[9]:

	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

Here we can see the mean and median("50%") are really far apart for order_amount. The standard deviation is also very high, meaning we have a wide spread distribution in order amounts.

This suggests there are expensive orders that are skewing the data to a higher $ value.

In [27]:

```
# Calculating the inncorrect method for average order value likley used
wrong_way = df.order_amount.mean()
print(wrong_way)
```

```
3145.128
```

This calculation is mathematically correct but the insight it provides is far from the truth. The median we saw described could possibly be a better insight as to what a typical order would look like, $284.

That is much more reasonable for the business context of a shoe store order compared to $3145.

To confirm my idea of outliers causing the skew, let's continue.

In [10]:

```
# Taking a look at the top 50 orders by order_amount
df.nlargest(50, ['order_amount'])
```

Out[10]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
15	16	42	607	704000	2000	credit_card	2017-03-07 4:00:00
60	61	42	607	704000	2000	credit_card	2017-03-04 4:00:00
520	521	42	607	704000	2000	credit_card	2017-03-02 4:00:00
1104	1105	42	607	704000	2000	credit_card	2017-03-24 4:00:00
1362	1363	42	607	704000	2000	credit_card	2017-03-15 4:00:00
1436	1437	42	607	704000	2000	credit_card	2017-03-11 4:00:00
1562	1563	42	607	704000	2000	credit_card	2017-03-19 4:00:00
1602	1603	42	607	704000	2000	credit_card	2017-03-17 4:00:00
2153	2154	42	607	704000	2000	credit_card	2017-03-12 4:00:00
2297	2298	42	607	704000	2000	credit_card	2017-03-07 4:00:00
2835	2836	42	607	704000	2000	credit_card	2017-03-28 4:00:00
2969	2970	42	607	704000	2000	credit_card	2017-03-28 4:00:00
3332	3333	42	607	704000	2000	credit_card	2017-03-24 4:00:00
4056	4057	42	607	704000	2000	credit_card	2017-03-28 4:00:00
4646	4647	42	607	704000	2000	credit_card	2017-03-02 4:00:00
4868	4869	42	607	704000	2000	credit_card	2017-03-22 4:00:00
4882	4883	42	607	704000	2000	credit_card	2017-03-25 4:00:00
691	692	78	878	154350	6	debit	2017-03-27 22:51:43
2492	2493	78	834	102900	4	debit	2017-03-04 4:37:34
1259	1260	78	775	77175	3	credit_card	2017-03-27 9:27:20
2564	2565	78	915	77175	3	debit	2017-03-25 1:19:35
2690	2691	78	962	77175	3	debit	2017-03-22 7:33:25
2906	2907	78	817	77175	3	debit	2017-03-16 3:45:46
3403	3404	78	928	77175	3	debit	2017-03-16 9:45:05
3724	3725	78	766	77175	3	credit_card	2017-03-16 14:13:26
4192	4193	78	787	77175	3	credit_card	2017-03-18 9:25:32
4420	4421	78	969	77175	3	debit	2017-03-09 15:21:35
4715	4716	78	818	77175	3	debit	2017-03-05 5:10:44
490	491	78	936	51450	2	debit	2017-03-26 17:08:19
493	494	78	983	51450	2	cash	2017-03-16 21:39:35
511	512	78	967	51450	2	cash	2017-03-09 7:23:14
617	618	78	760	51450	2	cash	2017-03-18 11:18:42
1529	1530	78	810	51450	2	cash	2017-03-29 7:12:01
2452	2453	78	709	51450	2	cash	2017-03-27 11:04:04
2495	2496	78	707	51450	2	cash	2017-03-26 4:38:52
2512	2513	78	935	51450	2	debit	2017-03-18 18:57:13
2818	2819	78	869	51450	2	debit	2017-03-17 6:25:51
2821	2822	78	814	51450	2	cash	2017-03-02 17:13:25
3101	3102	78	855	51450	2	credit_card	2017-03-21 5:10:34
3167	3168	78	927	51450	2	cash	2017-03-12 12:23:08

Answer 1A (summary)

In order amount, the largest orders are 704,000 confirming our outlier suspicions compared to the median of

$284. While these orders make up a small fraction of the 5,000 total orders for this period, the values are skewing the Average Order Value much higher.

Since we can also see the 704,000 outliers all share a common total_items of 2,000, we can say the shoes are reasonable when priced on an individual level: 704,000/2,000 = $352 per pair

This indicates that the high volume of total_items on these orders are the outlier causing $704,000 order_amounts.

Let's find a better way to analyze this data since we know outliers exist. Let's discriminate from orders of extreme volume or high 'total_items'(i.e. "2,000")

In [11]:

```
# Adding 'avg_item_cost' column to data
# 'avg_item_cost' is the average price per item for each order or "per capita cost"
df['avg_item_cost'] = df.order_amount.divide(df.total_items)
df.avg_item_cost.describe()
```

Out[11]:

```
count     5000.000000
mean       387.742800
std       2441.963725
min         90.000000
25%        133.000000
50%        153.000000
75%        169.000000
max      25725.000000
Name: avg_item_cost, dtype: float64
```

No more extreme volume cases, but this is not my answer. Mean is still far from median("50%")...

AHA! We found an outlier in price, according to the "max" value, an item worth $25,725 exists in the data. This is also an extreme outlier in order_amount but this time it's not caused by total_items.

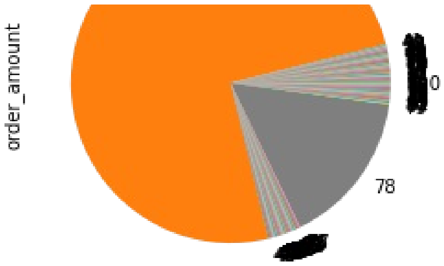
In [28]:

```
# To view the shops selling the most expensive items
pd.set_option('max_rows', 40)
order_amt_gb_shop = pd.DataFrame(df.groupby(['shop_id']).order_amount.mean())
print(order_amt_gb_shop.sort_values(by='order_amount', ascending = False))

# pie chart of each shop's shoe price relative to all 100 shops
order_amt_gb_shop.order_amount.plot.pie(x='order_amount', y='val', rot=0)
```

```
          order_amount
shop_id
42       235101.490196
78        49213.043478
50          403.545455
90          403.224490
38          390.857143
...                ...
53          214.117647
100         213.675000
32          189.976190
2           174.327273
92          162.857143

[100 rows x 1 columns]
```

Out[28]:

```
<AxesSubplot:ylabel='order_amount'>
```



The list and chart confirm that shop 42 & 78 are extreme outliers in price compared to other shops. While these are valid items being sold, we don't want them included to hijack our metrics.

Let's exclude them by not including the top and bottom 2.5% or taking the inner 95% of our item price data.

In [40]:

```
# Extract order amount grouped by shop percentiles
order_amt_gb_shop_4 = np.percentile(order_amt_gb_shop, 3.5)
order_amt_gb_shop_99 = np.percentile(order_amt_gb_shop, 98.5)

# including only the inner quartile range 95% of order amounts grouped by shop
oa_gbs_iqr = df[(df['order_amount']>= order_amt_gb_shop_4) & (df['order_amount']<= order
_amt_gb_shop_99)]
oa_gbs_iqr.describe()
```

Out[40]:

	order_id	shop_id	user_id	order_amount	total_items	avg_item_cost
count	3087.000000	3087.000000	3087.000000	3087.000000	3087.000000	3087.000000
mean	2494.936184	49.808876	848.490444	393.218659	2.573372	153.719469
std	1443.606315	28.777530	87.421487	138.018753	0.796365	30.570950
min	1.000000	1.000000	700.000000	222.000000	1.000000	90.000000
25%	1227.000000	24.000000	773.000000	296.000000	2.000000	133.000000
50%	2506.000000	50.000000	848.000000	352.000000	2.000000	153.000000
75%	3721.000000	74.000000	925.000000	468.000000	3.000000	168.000000
max	5000.000000	100.000000	999.000000	1760.000000	8.000000	352.000000

Answer 1B (summary)

The mean and median("50%") are now much closer, representing a more normal distribution. This means we excluded the extreme outliers. We are left with a much more accurate metric: An average order amount of 393 with an average item count of 2. Much more sensible!

Answer 1C

My metric's value is that it's a better representation of the majority of the data where previously the data's order amount was being skewed by including some extreme orders. The average of the orders from those inner 95% of stores are a more accurate depiction of the data from this period.

It is more important to look at the majority of the data not all of it. The inner data is there to tell a story while the outliers are the ones augmenting it.

BONUS INSIGHT:

What is the average user spending on orders, let's take a look.

In [7]:

```
# organized by each user, what the avg price of the item ordered
user_avg = df.groupby('user_id').avg_item_cost.mean()
user_avg.describe()
#INSGIGHT# 301 unique users
```

Out[7]:

```
count     301.000000
mean      398.638568
std       612.661697
min       134.933333
25%       148.421053
50%       152.826087
75%       158.850000
max      3162.235294
Name: avg_item_cost, dtype: float64
```

In [36]:

```
#largest 14 purchases by amount
df.nlargest(14, ['order_amount'])
```

Out[36]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at	avg_item_cost
15	16	42	607	704000	2000	credit_card	2017-03-07 4:00:00	352.0
60	61	42	607	704000	2000	credit_card	2017-03-04 4:00:00	352.0
520	521	42	607	704000	2000	credit_card	2017-03-02 4:00:00	352.0
1104	1105	42	607	704000	2000	credit_card	2017-03-24 4:00:00	352.0
1362	1363	42	607	704000	2000	credit_card	2017-03-15 4:00:00	352.0
1436	1437	42	607	704000	2000	credit_card	2017-03-11 4:00:00	352.0
1562	1563	42	607	704000	2000	credit_card	2017-03-19 4:00:00	352.0
1602	1603	42	607	704000	2000	credit_card	2017-03-17 4:00:00	352.0
2153	2154	42	607	704000	2000	credit_card	2017-03-12 4:00:00	352.0
2297	2298	42	607	704000	2000	credit_card	2017-03-07 4:00:00	352.0
2835	2836	42	607	704000	2000	credit_card	2017-03-28 4:00:00	352.0
2969	2970	42	607	704000	2000	credit_card	2017-03-28 4:00:00	352.0
3332	3333	42	607	704000	2000	credit_card	2017-03-24 4:00:00	352.0
4056	4057	42	607	704000	2000	credit_card	2017-03-28 4:00:00	352.0

The largest orders by order_amount are over 700,000 confirming our outlier suspisions compared to the median of $284. While these orders make up a small fraction of the 5,000 total orders for this period, the values are skewing the Average Order Value much higher.

Looking at the user_id column we can see that "user_id: 607" is resposible for all orders of the highest order_amount and total_items. Let's investigate...

In [20]:

```
# Calculating user 607's contribution to total items ordered in this period
user_607 = df[df.user_id == 607].total_items.count()/df.total_items.count()

# Calculating user 607's contribution to the total amount ordered ($) as a percentage
user_607_pct_total = df[df.user_id == 607].order_amount.sum()/df.order_amount.sum()

# Calculating user 607's contribution to the total amount ordered ($) in $
user_607_order_amount = df[df.user_id == 607].order_amount.sum()

user_607, user_607_pct_total, user_607_order_amount
```

Out[20]:

```
(0.0034, 0.7610501067047192, 11968000)
```

Although this user only made up 0.0034% of all orders, they contributed 76% of all the order amount ($)generated$ **11,968,000 worth of goods! Quite the shopper!** $.Theypurchased$