challenge_question1

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0.1 #### Shopify Data Science Intern Role Challenge

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.

- a. Think about what could be going wrong with our calculation. Think about a better way to evaluate this data.

- b. What metric would you report for this dataset?

-

0.2 c. What is its value?

[1]:
```
import altair as alt
import pandas as pd

alt.renderers.enable('png')
alt.renderers.enable('mimetype')
alt.data_transformers.enable('data_server')

# ignore chaining error
pd.options.mode.chained_assignment = None
```

Read Data This that is from the shopify challenge: Here is the URL to reproduce the code: Link

[2]:
```
# URL to reproduce the code
# URL = "https://docs.google.com/spreadsheets/d/
↪16i38oonuX1y1g7C_UAmiK9GkY7cS-64DfiDMNiR41LM/edit#gid=0"
```

```python
# FILE_PATH = "shofify_challenge/data/"

df = pd.read_csv("data/data.csv")
df.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 4:23:56
3  2017-03-26 12:43:37
4   2017-03-01 4:35:11
```

Data Information

- I will start with Data Information to check for missing values and data types of every feature

[3]:
```python
print("Data Information")
print("-------------------------")
df.info()
```

```
Data Information
-------------------------
<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   object
dtypes: int64(5), object(2)
memory usage: 273.6+ KB
```

- Since there are no missing values. I will convert the `order_id`, `shop_id`, `user_id` to categorical columns and create a new column: `unit_price`. ##### Munging and Wrangling

[4]:
```
df[["order_id", "shop_id", "user_id"]] = df[["order_id", "shop_id", "user_id"]].
  ↪astype(str)
df["unit_price"] = df["order_amount"] / df["total_items"]

print("After adding the new feature. This is what the dataframe looks like: ")
print("-------------------------")
df.head()
```

```
After adding the new feature. This is what the dataframe looks like:
-------------------------
```

[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

            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
```

I will move to the questions now

Question a : - A. Think about what could be going wrong with our calculation. Think about a better way to evaluate this data.

- I will start by computing the **AOV** for the dataset to see if we arrive at the same value

$$Average\ Order\ Value\ (AOV) = \frac{Total\ Revenue}{Total\ Order}$$

[5]:
```
total_revenue = df.order_amount.sum()
total_order = df.order_id.count()

aov = total_revenue/ total_order
print(f'AOV is : ${aov}')
```

```
AOV is : $3145.128
```

- I got the same AOV that was stated in the Problem Statement. I will go ahead to explore the dataset

0.3 ##### EXPLORE DATASET

[6]:
```
print("Descriptive statisitcs of Data")
print("-------------------------")
df.describe(include = "all")
```

```
Descriptive statisitcs of Data
-------------------------
```

[6]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method
count	5000	5000	5000	5000.000000	5000.00000	5000
unique	5000	100	301	NaN	NaN	3
top	1	53	718	NaN	NaN	credit_card
freq	1	68	28	NaN	NaN	1735
mean	NaN	NaN	NaN	3145.128000	8.78720	NaN
std	NaN	NaN	NaN	41282.539349	116.32032	NaN
min	NaN	NaN	NaN	90.000000	1.00000	NaN
25%	NaN	NaN	NaN	163.000000	1.00000	NaN
50%	NaN	NaN	NaN	284.000000	2.00000	NaN
75%	NaN	NaN	NaN	390.000000	3.00000	NaN
max	NaN	NaN	NaN	704000.000000	2000.00000	NaN

	created_at	unit_price
count	5000	5000.000000
unique	4991	NaN
top	2017-03-28 4:00:00	NaN
freq	3	NaN
mean	NaN	387.742800
std	NaN	2441.963725
min	NaN	90.000000
25%	NaN	133.000000
50%	NaN	153.000000
75%	NaN	169.000000
max	NaN	25725.000000

I observed that the - Standard Deviation of the `order_amount: 41,282.53` is larger than the mean of the `order_amount: 3145.13`. - The maximum order is very large : `704,000`.

I will probe further by plotting the distribution of the `total_order_amount` for the 100 shops.

[7]:
```
hist_order_amount = alt.Chart(df).mark_bar().encode(
    x=alt.X('order_amount', bin=alt.Bin(maxbins=50), title = "Order Amount"),
    y=alt.Y('count()' , title = 'Order Count Records')).properties(
    width=600,
    title = "Spread of Order Amount "
)
annot = df.copy()
annot['text'] = 'Mean Order Amount @ 3145.13'
```

```
rule = alt.Chart(df).mark_rule(color='red').encode(
    x ='mean(order_amount):Q'
)

text_annote_true = alt.Chart(annot).mark_text(color = 'red', dy=-150, dx=-220).
 ↪encode(
    text= 'text')

hist_order_amount + rule + text_annote_true
```

[7]:

- I obeserve that the distribution is right skewed with a largest percentage of the population far from the `mean order_amount`.

The following are probable reasons for the skewedness of the order amount population. - Wrongly input data. - Shops with higher order amount are pricey. - Shops with higher order amount pay more to get traffic to their store.

I will attempt to calculate the `AOV` for indivdual shops. I will demonstrate this below:

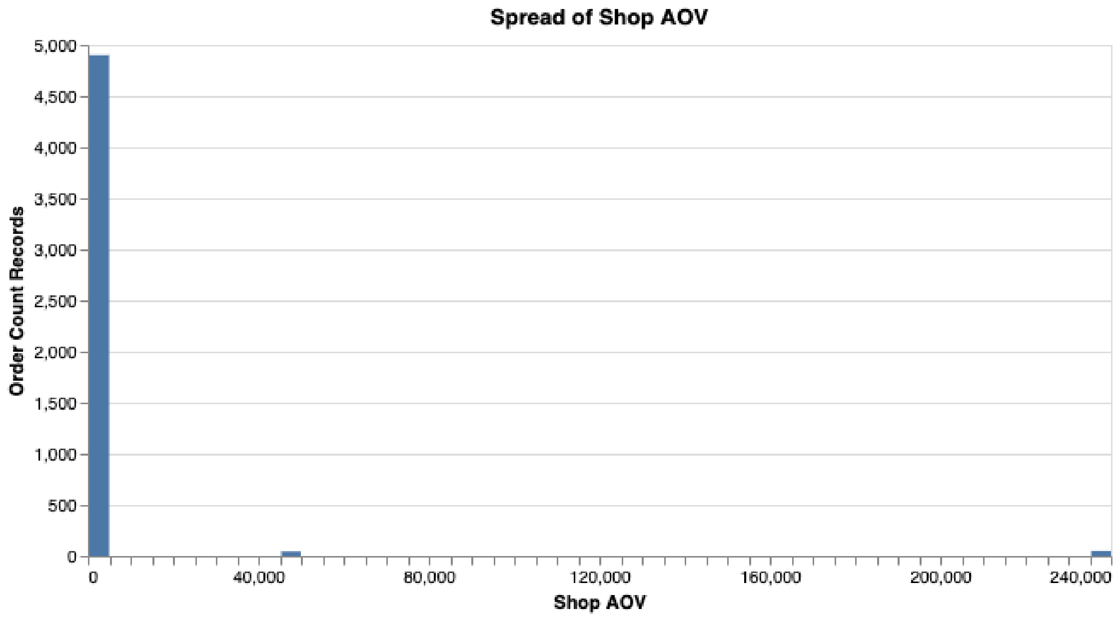
[8]:
```
# AOV for each store.
shop_aov = df.groupby('shop_id')["order_amount"].mean().reset_index()
shop_aov = shop_aov.rename(columns = {"order_amount":"shop_aov"})

# join the shop_aov table to the original df
merged_df = df.merge(shop_aov)
```

0.4 ##### Distribution of SHop AOV

[9]:
```
hist_shop_aov = alt.Chart(merged_df).mark_bar().encode(
    x=alt.X('shop_aov', bin=alt.Bin(maxbins=50), title = "Shop AOV"),
    y=alt.Y('count()' , title = 'Order Count Records')).properties(
    width=600,
    title = "Spread of Shop AOV"
)
hist_shop_aov
```

[9]:



The `Spread of Shop AOV` plot is very similiar to that of the `Spread of Order Amount`. I will conclude by saying, visually it appears that there are three groupings by eye balling: - Shops that have a AOV between 0 - 10,000 - Shops that have AOV between 40,000 and 60,000 - Shops that have AOV between 200,000 and 240,000

I will visualize the `shop aov` distribution for the three categories and with three numerical values in consideration:

- SHop AOV
- Order Amount
- Unit Price #### SHOP WITH AOV BETWEEN 0 and 10,000

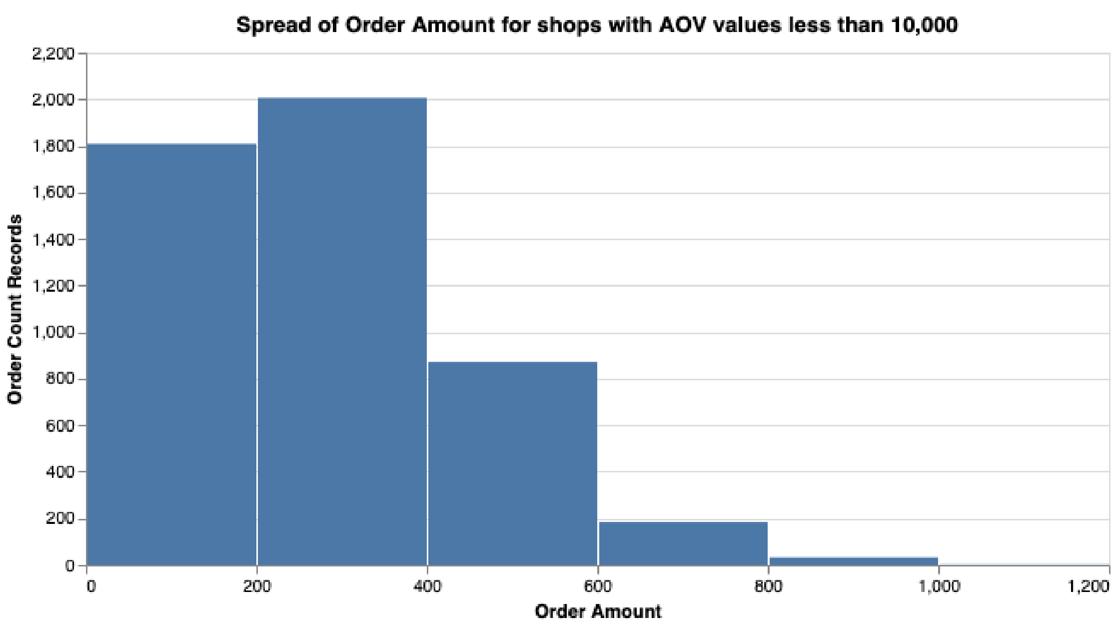
[10]:
```
less_than_10_000 = merged_df.query("shop_aov < 10000 ")
hist_shop_aov_10_000 = alt.Chart(less_than_10_000).mark_bar().encode(
    x=alt.X('shop_aov', bin=alt.Bin(maxbins=5), title = "Shop AOV"),
    y=alt.Y('count()' , title = 'Order Count Records')).properties(
    width=600,
    title = "Spread of Shop AOV for values less than 10,000"
)
```

```
hist_shop_aov_10_000
```

[10]:

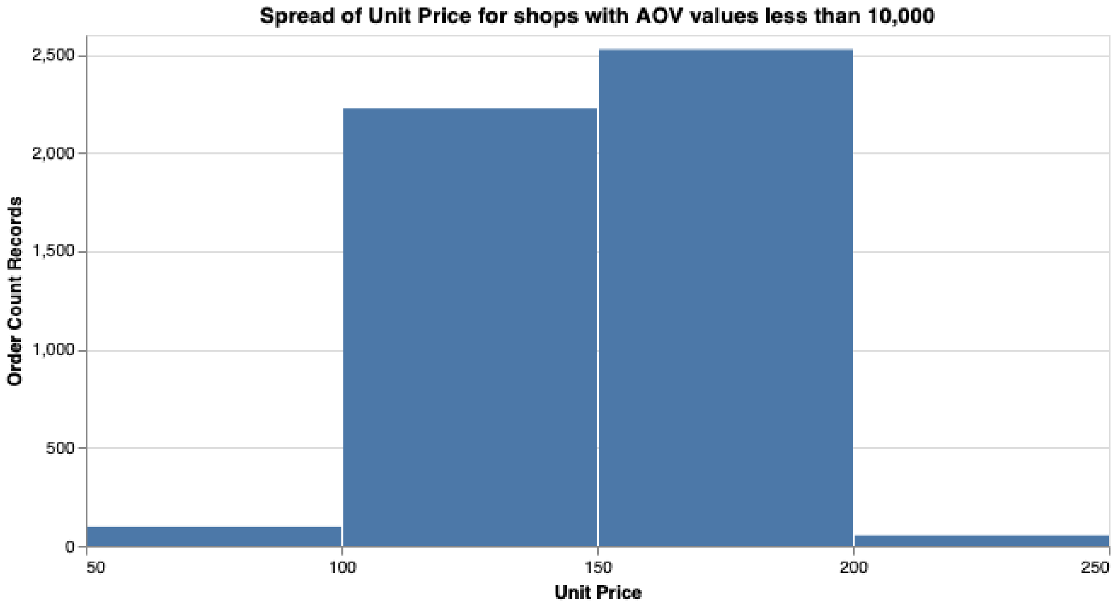

```
[11]: hist_order_amt_10_000 = alt.Chart(less_than_10_000).mark_bar().encode(
    x=alt.X('order_amount', bin=alt.Bin(maxbins=5), title = "Order Amount"),
    y=alt.Y('count()' , title = 'Order Count Records')).properties(
    width=600,
    title = "Spread of Order Amount for shops with AOV values less than 10,000"
)
hist_order_amt_10_000
```

[11]:



[12]:
```
hist_unit_price_10_000 = alt.Chart(less_than_10_000).mark_bar().encode(
    x=alt.X('unit_price', bin=alt.Bin(maxbins=5), title = "Unit Price"),
    y=alt.Y('count()' , title = 'Order Count Records')).properties(
    width=600,
    title = "Spread of Unit Price for shops with AOV values less than 10,000"
)
hist_unit_price_10_000
```

[12]:

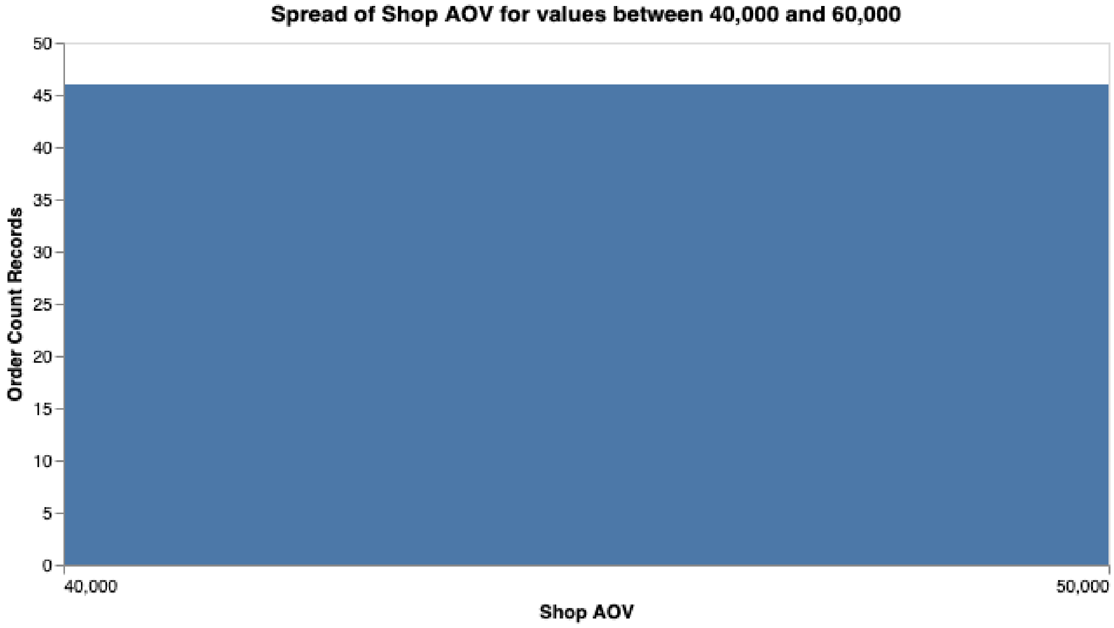


The distrubtion for the `Unit Price` and `Shop AOV` in the first category (less than 10,000) looks like an approximation of a normal distribution. This means that they sell very related prices. The `Order Amount` is right skewed and it is influenced by the total number of items purchased by the users. This is somewhat what is expect form a sample of the population.

SHOP WITH AOV BETWEEN 40,000 and 60,000

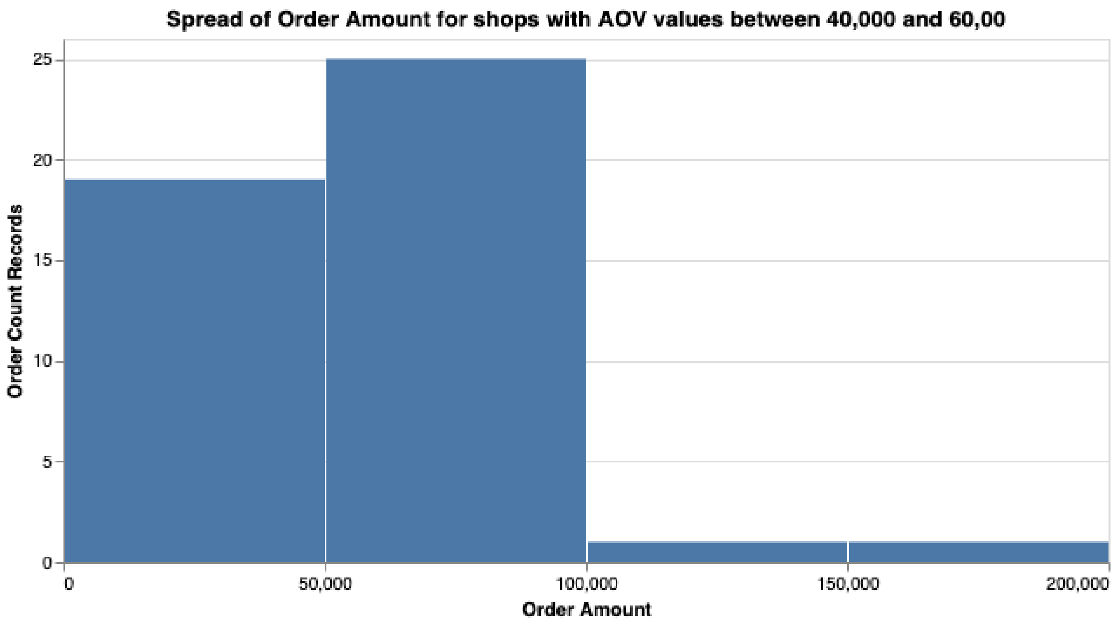
[13]:
```
less_than_60_000 = merged_df.query("shop_aov > 40_000 and shop_aov < 60_000 ")
hist_shop_aov_60_000 = alt.Chart(less_than_60_000).mark_bar().encode(
    x=alt.X('shop_aov', bin=alt.Bin(maxbins= 5), title = "Shop AOV"),
    y=alt.Y('count()' , title = 'Order Count Records')).properties(
    width=600,
    title = "Spread of Shop AOV for values between 40,000 and 60,000"
)
hist_shop_aov_60_000
```

[13]:



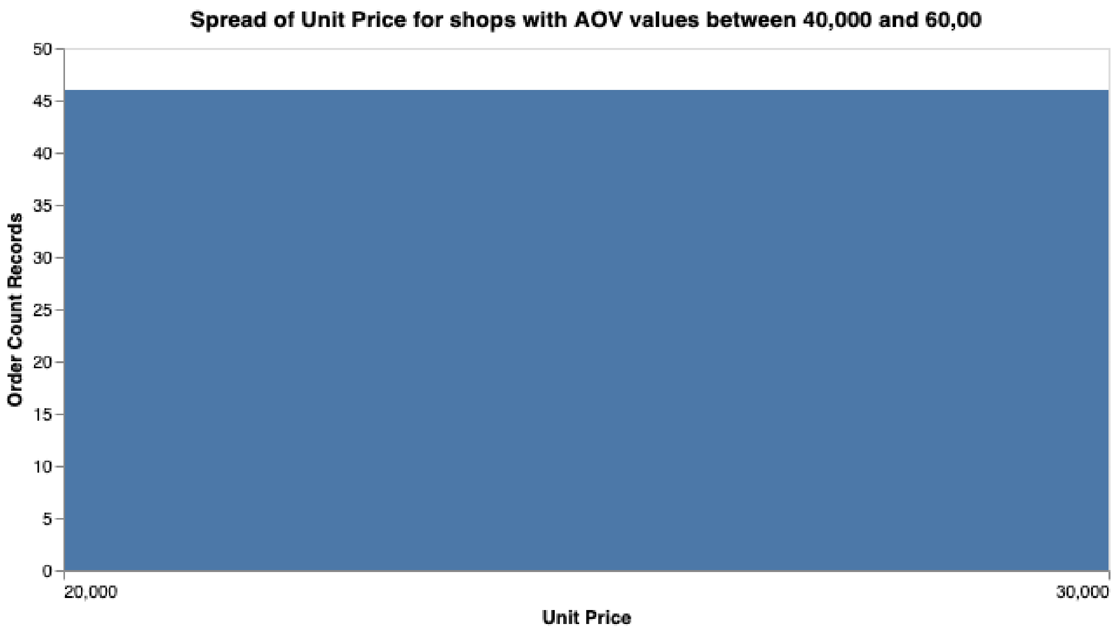
[14]:
```
less_than_60_000 = merged_df.query("shop_aov > 40_000 and shop_aov < 60_000 ")
hist_order_amt_60_000 = alt.Chart(less_than_60_000).mark_bar().encode(
    x=alt.X('order_amount', bin=alt.Bin(maxbins=5), title = "Order Amount"),
    y=alt.Y('count()' , title = 'Order Count Records')).properties(
    width=600,
    title = "Spread of Order Amount for shops with AOV values between 40,000␣
 ↪and 60,00"
)
hist_order_amt_60_000
```

[14]:



[15]:
```
hist_unit_price_60_000 = alt.Chart(less_than_60_000).mark_bar().encode(
    x=alt.X('unit_price', bin=alt.Bin(maxbins=5), title = "Unit Price"),
    y=alt.Y('count()' , title = 'Order Count Records')).properties(
    width=600,
    title = "Spread of Unit Price for shops with AOV values between 40,000 and␣
 ↪60,00"
)
hist_unit_price_60_000
```

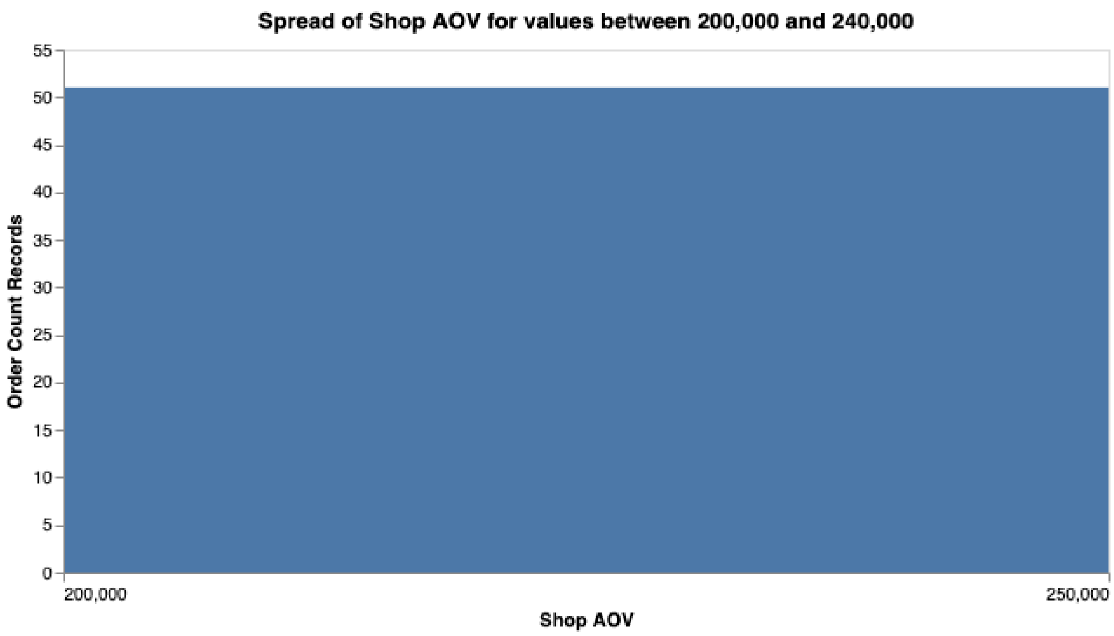
[15]:



The distrubtion for the second category for the `Unit Price` and `Shop AOV`(less than 60,000) looks like a uniform distribution. This is not what is expect frorm a sample of the population of Order history. This shows an outlier in the overall population. The `Order Amount` however is right skewed and it is influenced by the total number of items purchased by the users. #### SHOP WITH AOV MORE THAN 200,000

[16]:
```
less_than_200_000 = merged_df.query("shop_aov > 200_000 and shop_aov < 240_000␣
↪")
hist_shop_aov_200_000 = alt.Chart(less_than_200_000).mark_bar().encode(
    x=alt.X('shop_aov', bin=alt.Bin(maxbins= 5), title = "Shop AOV"),
    y=alt.Y('count()' , title = 'Order Count Records')).properties(
    width=600,
    title = "Spread of Shop AOV for values between 200,000 and 240,000"
)
hist_shop_aov_200_000
```

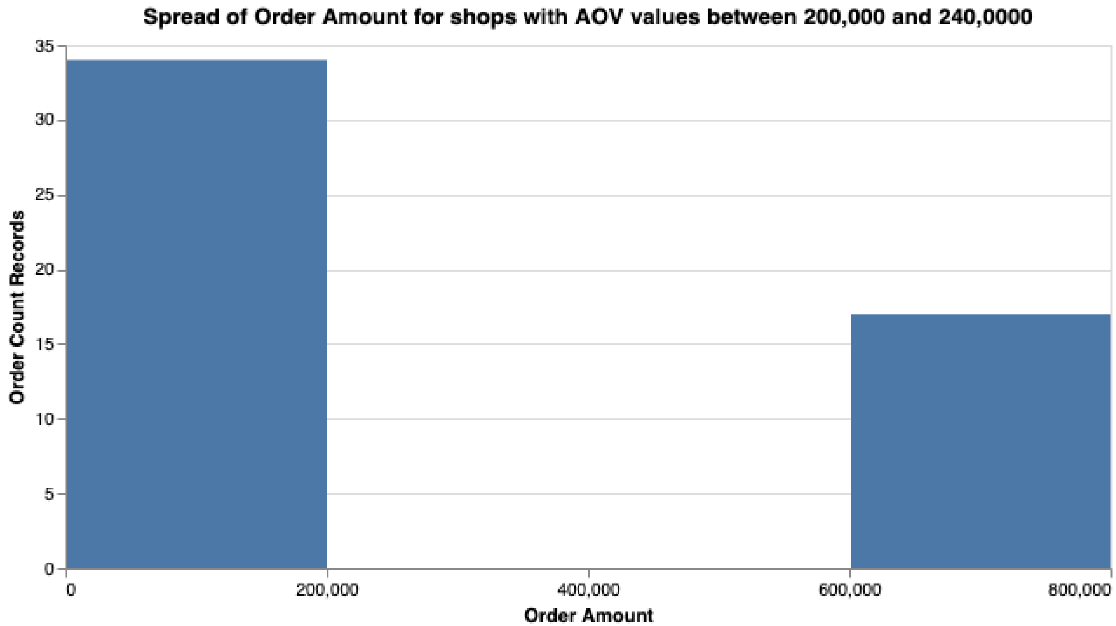
[16]:



[17]:
```
gt_than_200_000 = merged_df.query("shop_aov > 200_000")
hist_order_amt_200_000 = alt.Chart(gt_than_200_000).mark_bar().encode(
    x=alt.X('order_amount', bin=alt.Bin(maxbins=5), title = "Order Amount"),
    y=alt.Y('count()' , title = 'Order Count Records')).properties(
    width=600,
    title = "Spread of Order Amount for shops with AOV values between 200,000␣
↪and 240,0000"
)
```

```
hist_order_amt_200_000
```

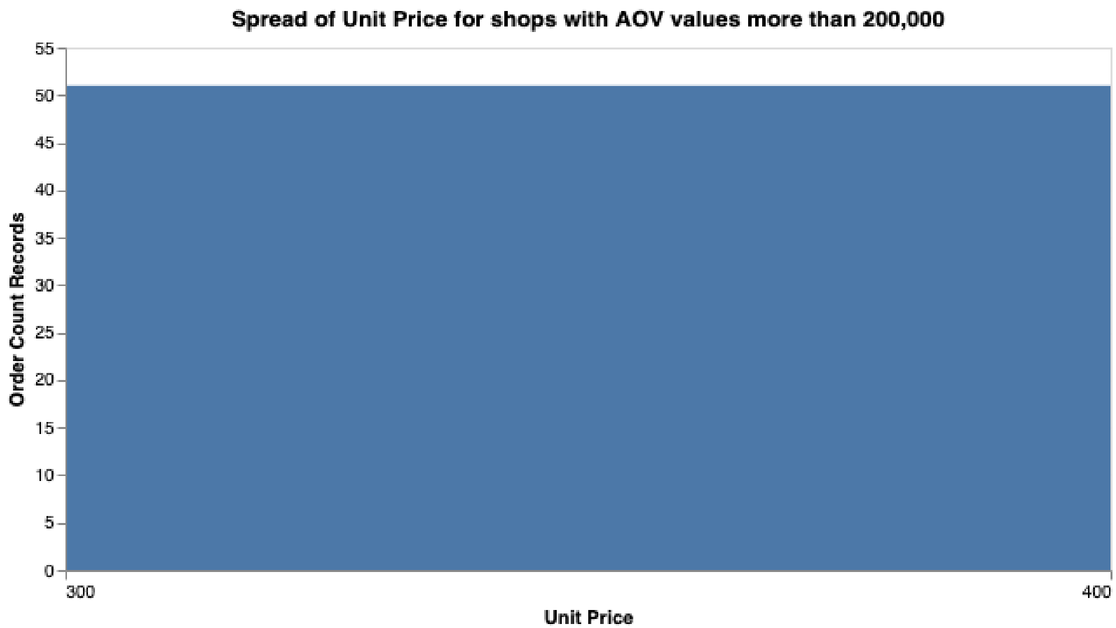
[17]:



[18]:

```
hist_unit_price_200_000 = alt.Chart(gt_than_200_000).mark_bar().encode(
    x=alt.X('unit_price', bin=alt.Bin(maxbins=5), title = "Unit Price"),
    y=alt.Y('count()' , title = 'Order Count Records')).properties(
    width=600,
    title = "Spread of Unit Price for shops with AOV values more than 200,000"
)
hist_unit_price_200_000
```

[18]:



In the distrubtion for the third category the `Unit Price` and `Shop AOV`(more than 200,000) looks like a uniform distribution. This is not what is expect from a sample of the population of Order history. This shows an outlier in the overall population. The `Order Amount` however is right skewed and it is influenced by the total number of items purchased by the users. #### SHOP WITH AOV MORE THAN 200,000

Think about a better way to evaluate this data. On that note, a better way to evaluate this dataset would be to remove the outliers and consider for the analysis only the shops that appear to have normally distributed `AOV`.

A standard way to detect outliers will be to use the inter quartile range as a yardstick. I will remove from the observation shops whose unit price is such that:

$$UnitPrice < Q1 - 1.5 * IQR(UnitPrice)$$

OR

$$UnitPrice > Q1 + 1.5 * IQR(UnitPrice)$$

[19]:
```python
def remove_outlier(df, col):
    """
    Remove outlier form data frame
    using Inter Quartile range

    Paramters
    ---------
    df: DataFrame (pd.DataFrame)
    col: numeric column (int)

```

```
    Return
    ------
    DataFrame (pd.DataFrame)

    Example
    -------
    >>> remove(merged_df, 'unit_price')
    """
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)

    IQR = Q3 - Q1

    low_value  = Q1 - 1.5 * IQR
    high_value  = Q3 + 1.5 * IQR

    new_df = df.loc[(df[col] > low_value) & (df[col] < high_value)]
    return new_df
```

The credit for the function above `remove_outlier` : Stackoverflow

[20]:
```
print(f"Shops Considering for the Analysis Are \
    {remove_outlier(merged_df, 'unit_price').shop_id.nunique()}")
```

```
Shops Considering for the Analysis Are     98
```

Hence , out of the 100 shops I will be considering 98 shops for the analysis

0.5 ##### Question b: What metric would you report for this dataset?

I will be using the `AOV` as the metric this is because of the limited information from the data. I would like to mention other metrics I might have considered out the `AOV`.

I will like to consider `LTV- Life Time Value` and `CAC-Customer Aquisition Cost`. But I will rule them out because the data does not tell us about the Aquisition cost for each shop for that month and does not tell us about the margin. The reason for considering Customer's LTV and CAC is because I believe the data gives sufficient information about this metric.

mean AOV for the Categories with less than 10,000 Shop AOV

[21]:
```
print(f"The mean AOV for the shop's with AOV is : ${less_than_10_000.shop_aov.
  ↪mean()}")
```

```
The mean AOV for the shop's with AOV is : $300.1558229655313
```

Question c: What is its value? The AOV has a value of approximately is `$300.16`