Data Visualization Final Project

Rusi Rothschild and Chashy Luria

My partner and I used a dataset from Kaggle containing data about coffee shop daily revenue. This dataset consists of 2000 rows of data from myriad coffee shops, making it robust and good for data analysis and visualization.

There are 7 features in the coffee shop dataset:

1. **Number of Customers Per Day-** The total number of customers visiting the coffee shop on any given day.
2. **Average Order Value ($)-** The average amount spent by each customer during their visit.
3. **Operating Hours Per Day-** The total number of hours the coffee shop is open for business each day.
4. **Number of Employees-** The number of employees working on a given day.
5. **Marketing Spent Per Day ($)-** The amount of money spent on marketing campaigns or promotions on any given day.
6. **Location Foot Traffic (people/hour**)- The number of people passing by the coffee shop per hour.
7. **Daily Revenue ($)-** This is the dependent variable representing the total revenue generated by the coffee shop each day.

Some of the questions we would like to answer while analyzing the data

- Does more **location foot traffic** correlate to a higher **number of customers per day**? Does a prime location attract more customers? Is a better location worth the rent?
- How much of an effect does **operation hours per day** have on the **daily revenue**? If the shop stays open for more hours, does that necessarily mean that the shop will make more money?
- Does the **number of employees** affect the **number of customers per day**? Would people rather go to a store that is adequately staffed?
- How does the amount of **money spent on marketing** affect the **daily revenue**? Does the money spent on marketing strategies succeed in raising the daily revenue?
- How do the **number of customers per day** and the **average order value** correlate with the **daily revenue**? Do more customers breed more revenue, or does the average order value have a larger significance on the daily revenue?

Importing and cleaning the data

1. We decided to clean the data using Python and uploaded the dataset to jupyter for easy preview and processing.

```
]: import pandas as pd
   data = pd.read_csv("coffee_shop_revenue.csv")
```

2. Preview the first 5 rows of this large dataset to get a feel of the dataset.

```
[ ] data.head()
```

	Number_of_Customers_Per_Day	Average_Order_Value	Operating_Hours_Per_Day	Number_of_Employees	Marketing_Spend_Per_Day	Location_Foot_Traffic	Daily_Revenue
0	152	6.74	14	4	106.62	97	1547.81
1	485	4.50	12	8	57.83	744	2084.68
2	398	9.09	6	6	91.76	636	3118.39
3	320	8.48	17	4	462.63	770	2912.20
4	156	7.44	17	2	412.52	232	1663.42

3. Check the length of the dataset; how many rows are we dealing with?

```
[ ] len(data)
```

```
2000
```

4. Check for any null values and proceed with dropping that data. Coffee shop revenue does not contain any null values.

```
print(data.isnull().sum())
```

```
Number_of_Customers_Per_Day    0
Average_Order_Value            0
Operating_Hours_Per_Day        0
Number_of_Employees            0
Marketing_Spend_Per_Day        0
Location_Foot_Traffic          0
Daily_Revenue                  0
dtype: int64
```

5. Check for any duplicate values and proceed with deleting those repetitious values. Coffee shop revenue does not contain any duplicate values.

```
[ ] print(data.duplicated().sum())
```

```
0
```

6. Use the info function to provide a summary of the pandas dataframe that we are working with. The output tells us a number of things.
    - The dataset consists of 2000 rows and 7 columns
    - Lists all column names along with their data types

- Shows the number of non null values per column
- This dataset uses 109.5 KB of memory

```
[ ] data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 7 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Number_of_Customers_Per_Day  2000 non-null   int64  
 1   Average_Order_Value          2000 non-null   float64
 2   Operating_Hours_Per_Day      2000 non-null   int64  
 3   Number_of_Employees          2000 non-null   int64  
 4   Marketing_Spend_Per_Day      2000 non-null   float64
 5   Location_Foot_Traffic        2000 non-null   int64  
 6   Daily_Revenue                2000 non-null   float64
dtypes: float64(3), int64(4)
memory usage: 109.5 KB
```

7. Use the describe function to provide a statistical summary of the numeric columns in the dataset.
    - Count >> all columns have 2000 entries; there are no null values.
    - Mean >> tells the average value for each column.
    - Standard deviation >> tells how wide the spread of values is.
    - Min and max values
    - Percentiles >> 25%, 50% and 75%

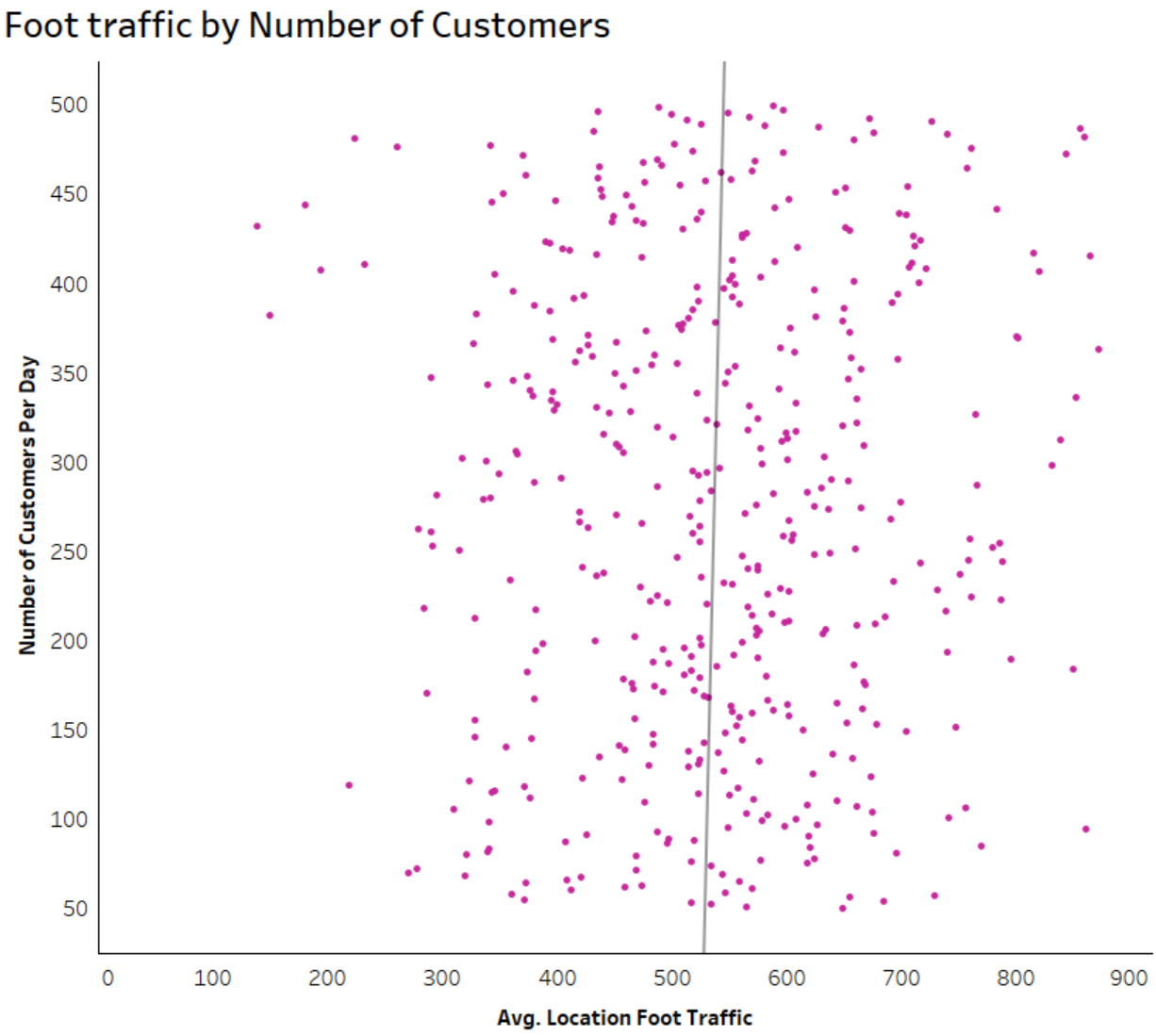
```
print(data.describe(include='all'))
```

```
       Number_of_Customers_Per_Day  Average_Order_Value  \
count                  2000.000000          2000.000000   
mean                    274.296000             6.261215   
std                     129.441933             2.175832   
min                      50.000000             2.500000   
25%                     164.000000             4.410000   
50%                     275.000000             6.300000   
75%                     386.000000             8.120000   
max                     499.000000            10.000000   

       Operating_Hours_Per_Day  Number_of_Employees  Marketing_Spend_Per_Day  \
count              2000.000000          2000.000000              2000.000000   
mean                 11.667000             7.947000               252.614160   
std                   3.438608             3.742218               141.136004   
min                   6.000000             2.000000                10.120000   
25%                   9.000000             5.000000               130.125000   
50%                  12.000000             8.000000               250.995000   
75%                  15.000000            11.000000               375.352500   
max                  17.000000            14.000000               499.740000   

       Location_Foot_Traffic  Daily_Revenue  
count            2000.000000    2000.000000  
mean              534.893500    1917.325940  
std               271.662295     976.202746  
min                50.000000     -58.950000  
25%               302.000000    1140.085000  
50%               540.000000    1770.775000  
75%               767.000000    2530.455000  
max               999.000000    5114.600000  
```

1. Foot traffic by number of customers: Analysis



Does more location foot traffic correlate to a higher number of customers per day?

Since we are looking to visualize the relationship between two continuous numerical variables, we decided to use a scatter plot. This will help us identify any correlations between the two measures. Scatter plots are also extremely helpful in detecting any outliers.

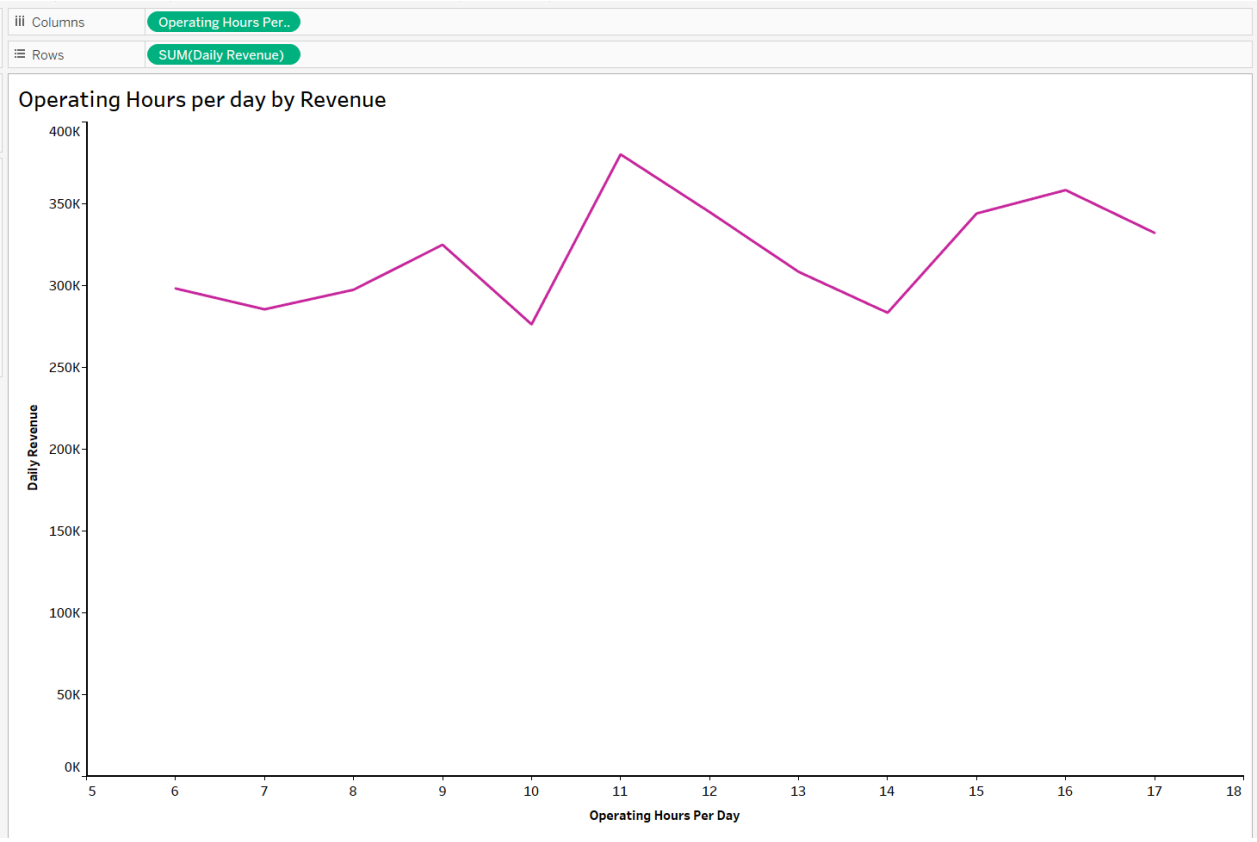
Analysis

The trend line suggests a very slight positive correlation between foot traffic and number of customers per day. This indicates that locations with higher foot traffic tend to have more customers, but the relationship is not very strong.

We also notice that there is a high variability; a wide spread of data. The data points are scattered about widely. This indicates that other factors besides foot traffic influence customer count. Further analysis will help us know what variables have a more significant effect on the customer count.

There appears to be a dense grouping of points between 400 and 700 location foot traffic, and 100 and 300 customers. There are a few outliers, where customer counts are significantly higher or lower that expected for a given foot traffic.

2. Operating Hours per day by Revenue: Analysis



How much of an effect does operation hours per day have on the daily revenue? If the shop stays open for more hours, does that necessarily mean that the shop will make more money?

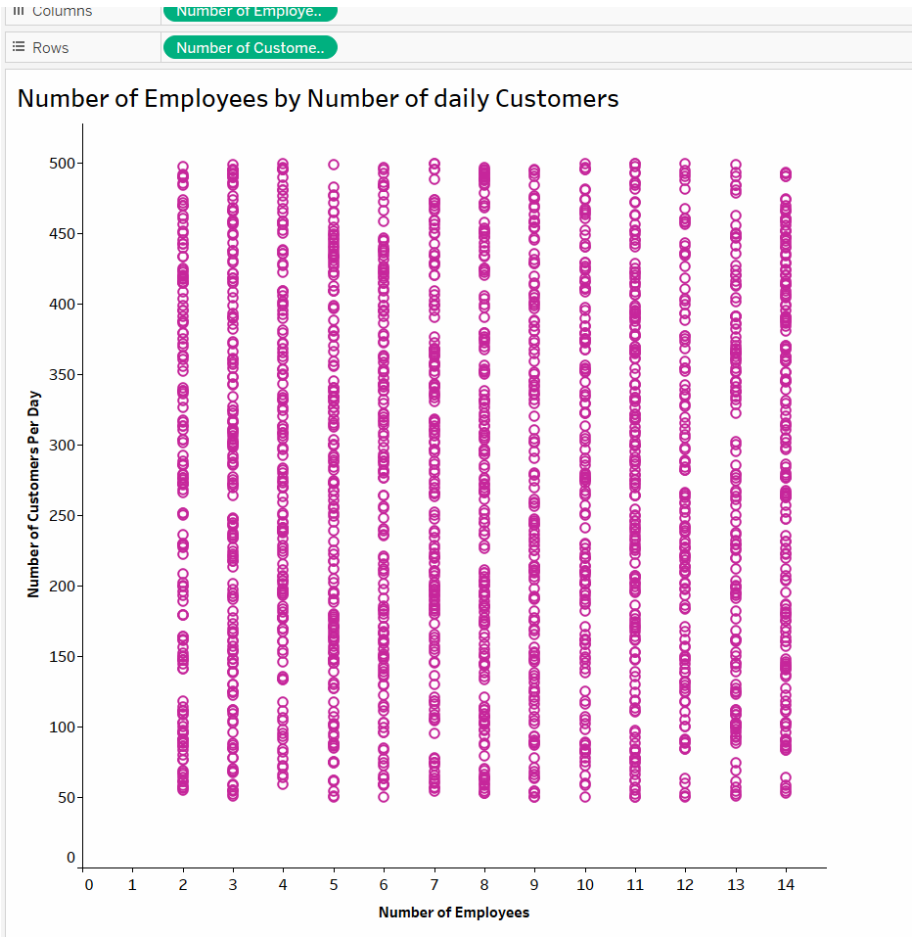
We placed operating hours per day in the columns and the sum of daily revenue in the rows. Using these to numerical measures, we created a line graph. To enhance clarity, we set the axis labels and titles to bold black for a sharp, professional look. We also removed grid lines and styled the line in pink to match the workbook's color scheme.

Analysis

The graph reveals that revenue peaks around 11-12 operating hours per day before declining and then rising again at 15-16 hours per day. While there is a slight upward trend, revenue fluctuates rather than increasing steadily with more operating hours, indicating that more hours do not always lead to higher revenue. This suggests that additional factors influence revenue beyond just operating hours.

Although this visualization may initially seem unhelpful, it actually provides valuable insights for businesses looking to increase revenue. While it might appear that staying open longer leads to higher earnings, the data reveals that other factors have a stronger impact on revenue.

3. Employee count by daily customers: Analysis



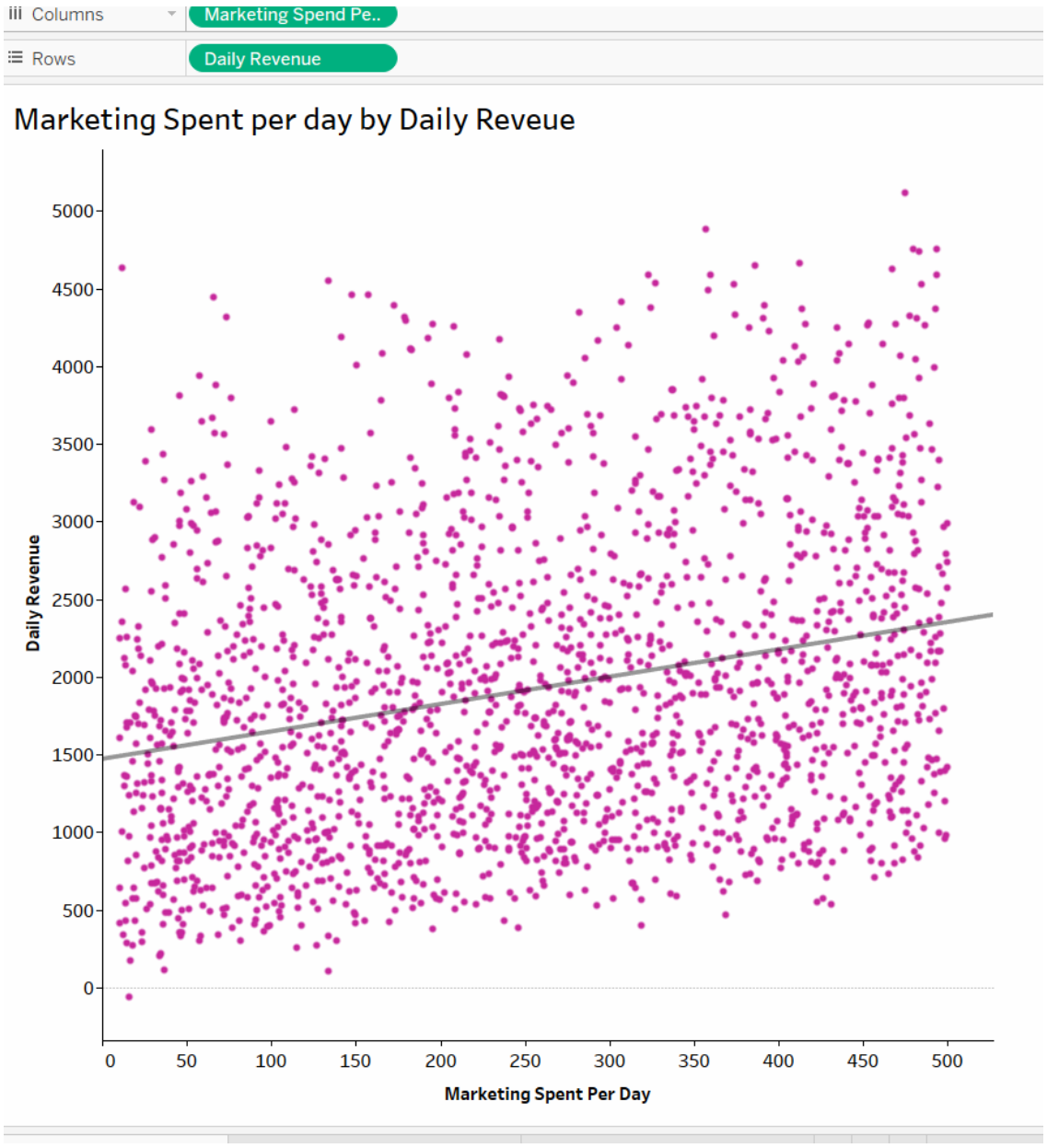
Does the number of employees affect the number of customers per day? Would people rather go to a store that is adequately staffed?

Again, since we are dealing with 2 numerical valuables, we will use a scatter plot to provide insight.

ANALYSIS

The distribution of data points, or lack thereof, suggests that having more employees does not strongly correlate with an increase in customers. While staffing levels vary, the customer count appears to fluctuate independently. This implies that other factors might be more influential in driving customer traffic rather than just the number of employees present.

4. Marketing Spent per day by Daily Revenue: Analysis



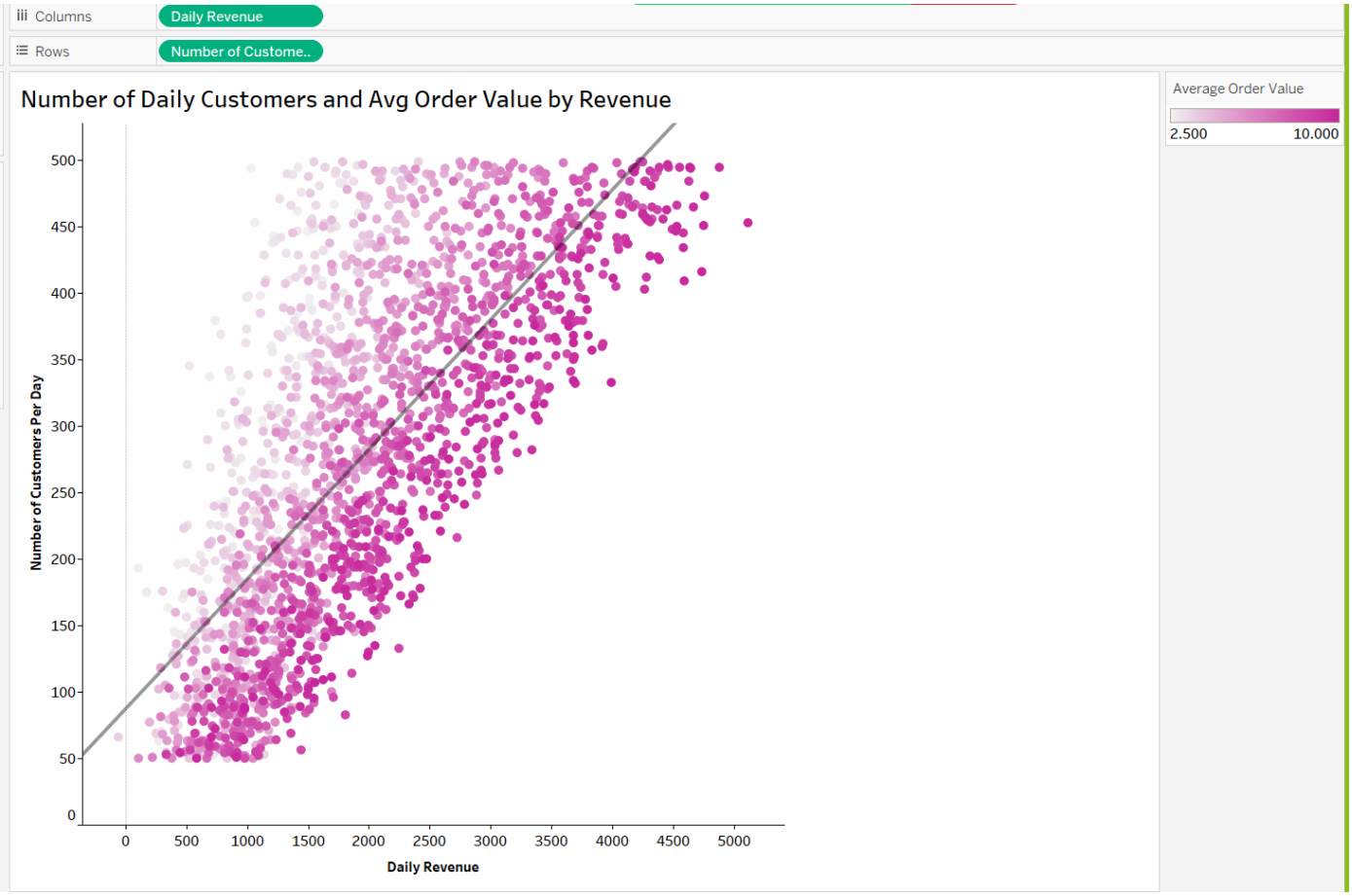
How does the amount of money spent on marketing affect the number of customers per day? Does the money spent on marketing strategies succeed in drawing in more customers?

ANALYSIS

Since we are dealing with 2 numeric values, we will use a scatter plot to answer this question. I placed the marketing spend per day along the X-axis and the daily revenue along the Y-axis. The scatter plot indicates a weak positive correlation. The higher marketing spending generally leads to increased revenue, but the effect is not very strong.

The data points are widely scattered, suggesting that other factors also play a role in revenue generation.

5. Number of Daily Customers and Average Order Value by Revenue: Analysis



How do the number of customers per day and the average order value correlate with the daily revenue? Do more customers breed more revenue, or does the average order value have a larger significance on the daily revenue?

Since we are dealing with 2 numeric values, we will use a scatter plot to answer this question. We placed Daily Revenue on the Columns shelf and Number of Customers Per Day on the Rows shelf, with Average Order Value assigned to the color bucket. This setup created a scatter plot, enhanced with a trend line for better visual analysis. To match our workbook's color scheme, we assigned pink to the data points, while using a contrasting black trend line to make it stand out and draw attention.

Analysis

The scatter plot and trendline show a clear positive relationship between Daily Revenue and Number of Customers—more customers lead to higher revenue. The color gradient also highlights that higher Average Order Values (darker shades) contribute to increased revenue. This is likely because higher revenue results not only from more customers, but also from a higher average order value.

While the correlation is strong, there is variation in the data. This is largely due to variability of the average order value, which is apparent when looking at the color gradient. Besides the average order value, there are also other also other factors that influence daily revenue.

Business Implications:

- Focus on Customer Acquisition: Increasing the number of customers is a key driver of revenue.
- Increase Average Order Value: Strategies to encourage customers to spend more per order should be explored.
- Analyze High-Performing Days: Investigate the days with high revenue, high customer count, and high average order value to understand the factors contributing to their success.

Ethical Implications:

1. Privacy and Data Sensitivity

Even though this dataset appears to focus on business operations, it may contain sensitive business performance data, such as revenue trends and customer traffic. If the dataset includes personally identifiable information (PII), sharing or analyzing it without proper authorization could violate confidentiality agreements.

Mitigation:

- Ensure that all data used for analysis is anonymized and does not expose sensitive business details.
- Obtain necessary permissions before using or sharing the data externally.

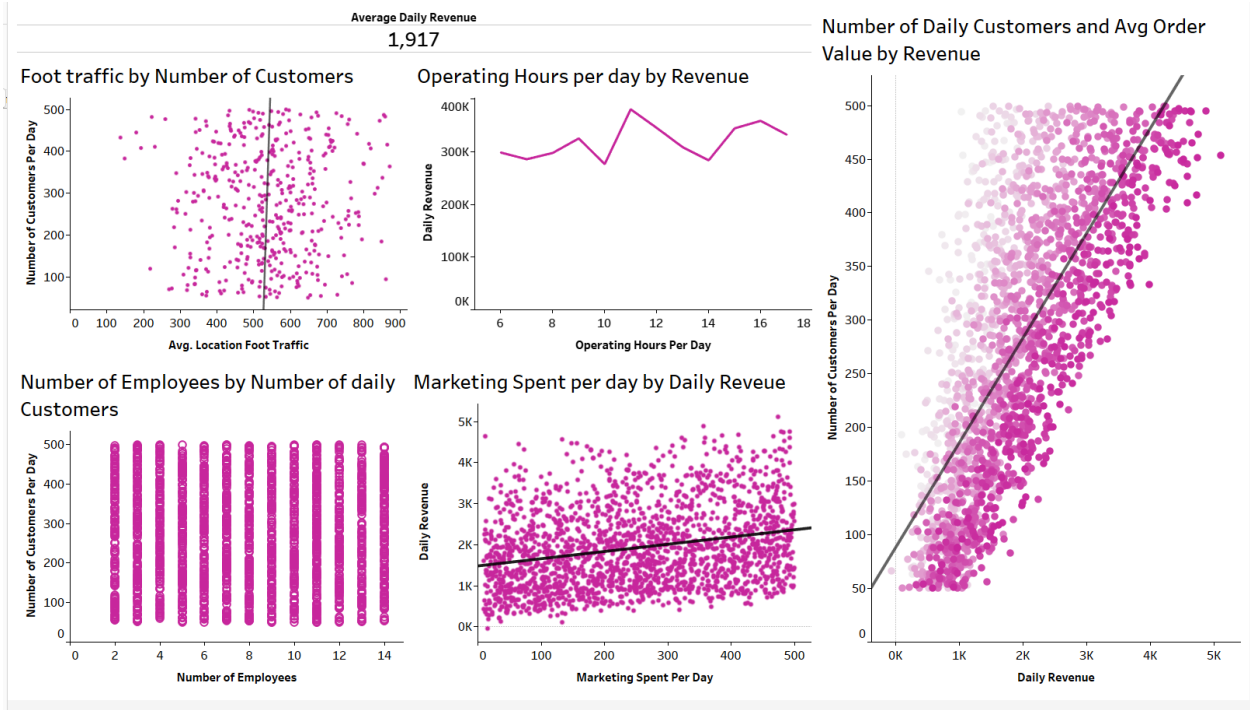
2. Misrepresentation and Bias

Data can sometimes be interpreted in misleading ways, especially if key factors influencing revenue (e.g., seasonal trends, location variations, or external economic factors) are not considered. If conclusions are drawn without acknowledging potential biases, they could lead to incorrect business decisions.

Mitigation:

- Provide context for any analysis, ensuring that all relevant factors are considered.
- Avoid cherry-picking data points that support a particular narrative while ignoring those that contradict it.
- Use visualizations and statistical methods to validate findings before making claims about causation

Dashboard:



We started by creating a KPI named Average Daily Revenue, displaying its value prominently. Next, we incorporated five visualizations, making the fifth one the largest since it provides the most critical insights, highlighting the two variables with the greatest impact on revenue. Finally, we ensured that each visualization was interactive, allowing viewers to explore the data and extract meaningful insights from the dashboard.

The word document, tableau visualizations, and power point were completed by both of us together on zoom. We attempted to delegate jobs, but alas, two brains are better than one, and we worked more efficiently together.