Quantium2

December 30, 2023

1 Importing Libraries

[1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats
from scipy.stats import ttest_ind
from scipy.stats import pearsonr
```

2 Loading and Exploring Dataset

[2]:

```
df = pd.read_csv("C:/Users/Asus/Desktop/Forage/QUANTIUM DA VIRTUAL INTERNSHIP/
 ↪QVI_data.csv")

print(df.head())  # Display the first few rows of the DataFrame

print(df.describe())  # Display basic statistics of the data

print(df.info())  # Check data types and missing values
```

```
   LYLTY_CARD_NBR        DATE  STORE_NBR  TXN_ID  PROD_NBR  \
0            1000  10/17/2018          1       1         5
1            1002   9/16/2018          1       2        58
2            1003    3/7/2019          1       3        52
3            1003    3/8/2019          1       4       106
4            1004   11/2/2018          1       5        96

                                PROD_NAME  PROD_QTY  TOT_SALES  PACK_SIZE  \
0  Natural Chip        Compny SeaSalt175g         2        6.0        175
1   Red Rock Deli Chikn&Garlic Aioli 150g         1        2.7        150
2   Grain Waves Sour    Cream&Chives 210G         1        3.6        210
3  Natural ChipCo      Hony Soy Chckn175g         1        3.0        175
4          WW Original Stacked Chips 160g         1        1.9        160

        BRAND              LIFESTAGE PREMIUM_CUSTOMER
0     NATURAL  YOUNG SINGLES/COUPLES          Premium
```

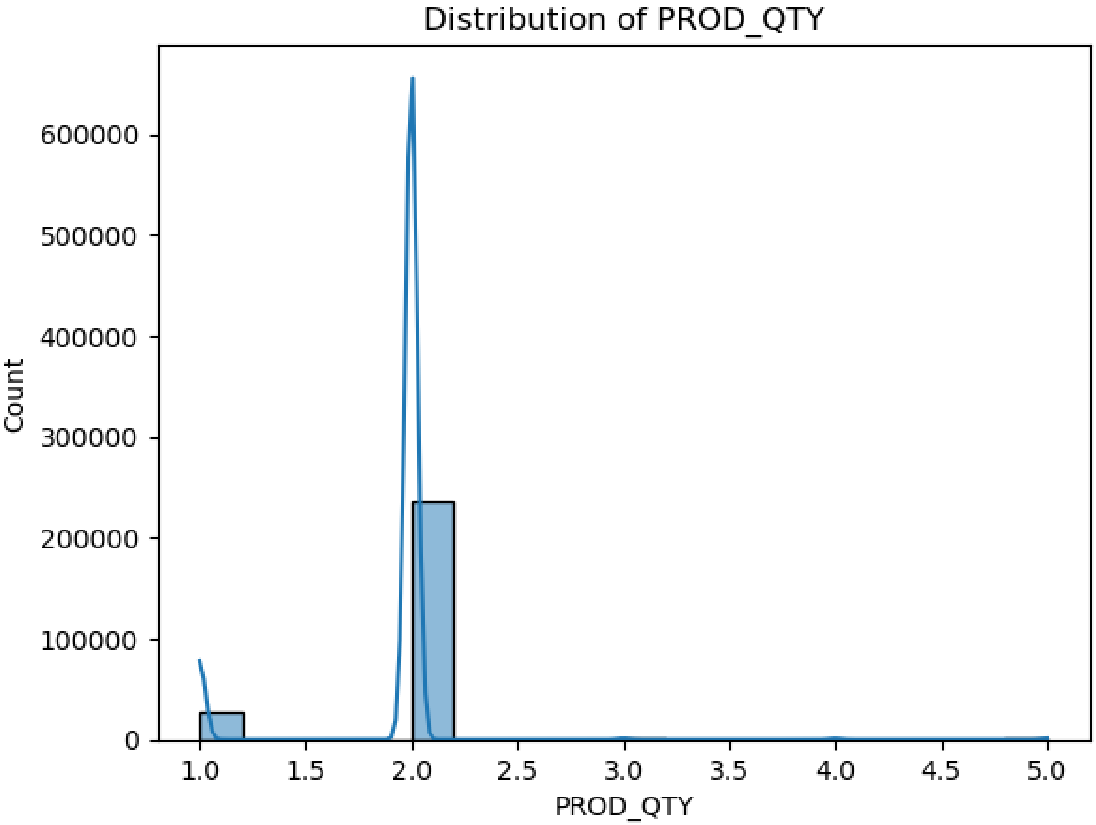
```
1         RRD  YOUNG SINGLES/COUPLES       Mainstream
2     GRNWVES         YOUNG FAMILIES           Budget
3     NATURAL         YOUNG FAMILIES           Budget
4  WOOLWORTHS  OLDER SINGLES/COUPLES       Mainstream
       LYLTY_CARD_NBR      STORE_NBR        TXN_ID       PROD_NBR  \
count    2.648340e+05  264834.000000  2.648340e+05  264834.000000
mean     1.355488e+05     135.079423  1.351576e+05      56.583554
std      8.057990e+04      76.784063  7.813292e+04      32.826444
min      1.000000e+03       1.000000  1.000000e+00       1.000000
25%      7.002100e+04      70.000000  6.760050e+04      28.000000
50%      1.303570e+05     130.000000  1.351365e+05      56.000000
75%      2.030940e+05     203.000000  2.026998e+05      85.000000
max      2.373711e+06     272.000000  2.415841e+06     114.000000

            PROD_QTY      TOT_SALES      PACK_SIZE
count  264834.000000  264834.000000  264834.000000
mean        1.905813       7.299346     182.425512
std         0.343436       2.527241      64.325148
min         1.000000       1.500000      70.000000
25%         2.000000       5.400000     150.000000
50%         2.000000       7.400000     170.000000
75%         2.000000       9.200000     175.000000
max         5.000000      29.500000     380.000000
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264834 entries, 0 to 264833
Data columns (total 12 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   LYLTY_CARD_NBR    264834 non-null  int64
 1   DATE              264834 non-null  object
 2   STORE_NBR         264834 non-null  int64
 3   TXN_ID            264834 non-null  int64
 4   PROD_NBR          264834 non-null  int64
 5   PROD_NAME         264834 non-null  object
 6   PROD_QTY          264834 non-null  int64
 7   TOT_SALES         264834 non-null  float64
 8   PACK_SIZE         264834 non-null  int64
 9   BRAND             264834 non-null  object
 10  LIFESTAGE         264834 non-null  object
 11  PREMIUM_CUSTOMER  264834 non-null  object
dtypes: float64(1), int64(6), object(5)
memory usage: 24.2+ MB
None
```

3 Identifying and Handling Outliers

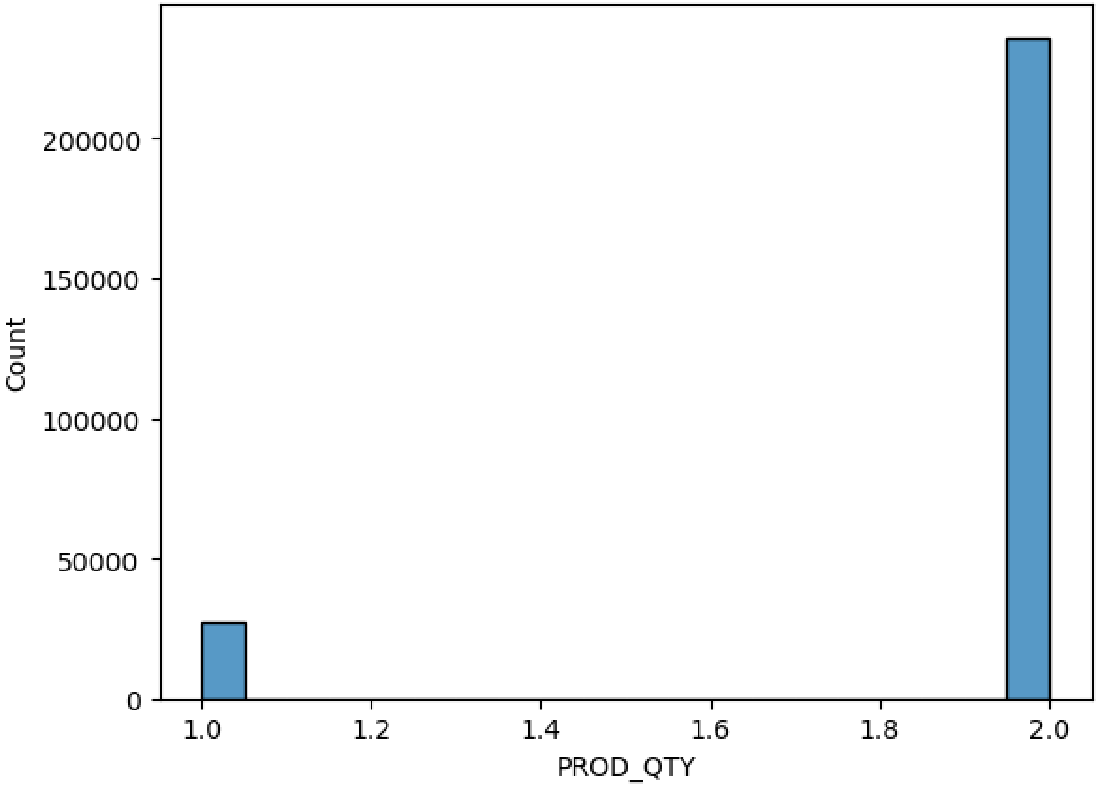
[3]:

```
## Visualize the distribution of the variable of interest (e.g., 'spend')
sns.histplot(df['PROD_QTY'], kde=True)
plt.title('Distribution of PROD_QTY')
plt.show()

# Calculate Z-scores
z_scores = np.abs(stats.zscore(df['PROD_QTY']))

# Define a threshold for identifying outliers (e.g., Z-score > 3)
outliers = (z_scores > 3)

# Identify and print the outliers
outlier_values = df['PROD_QTY'][outliers]
print("Outlier values:")
print(outlier_values)

# Remove outliers from the dataset
df_no_outliers = df[~outliers]

# Display the box plot after removing outliers for comparison
sns.histplot(x=df_no_outliers['PROD_QTY'])
plt.show()



## Visualize the distribution of the variable of interest (e.g., 'spend')
sns.histplot(df['TOT_SALES'], kde=True)
plt.title('Distribution of TOT_SALES')
plt.show()

# Calculate Z-scores
z_scores = np.abs(stats.zscore(df['PROD_QTY']))

# Define a threshold for identifying outliers (e.g., Z-score > 3)
outliers = (z_scores > 3)

# Identify and print the outliers
outlier_values = df['TOT_SALES'][outliers]
print("Outlier values:")
print(outlier_values)

# Remove outliers from the dataset
df_no_outliers = df[~outliers]

# Display the box plot after removing outliers for comparison
```

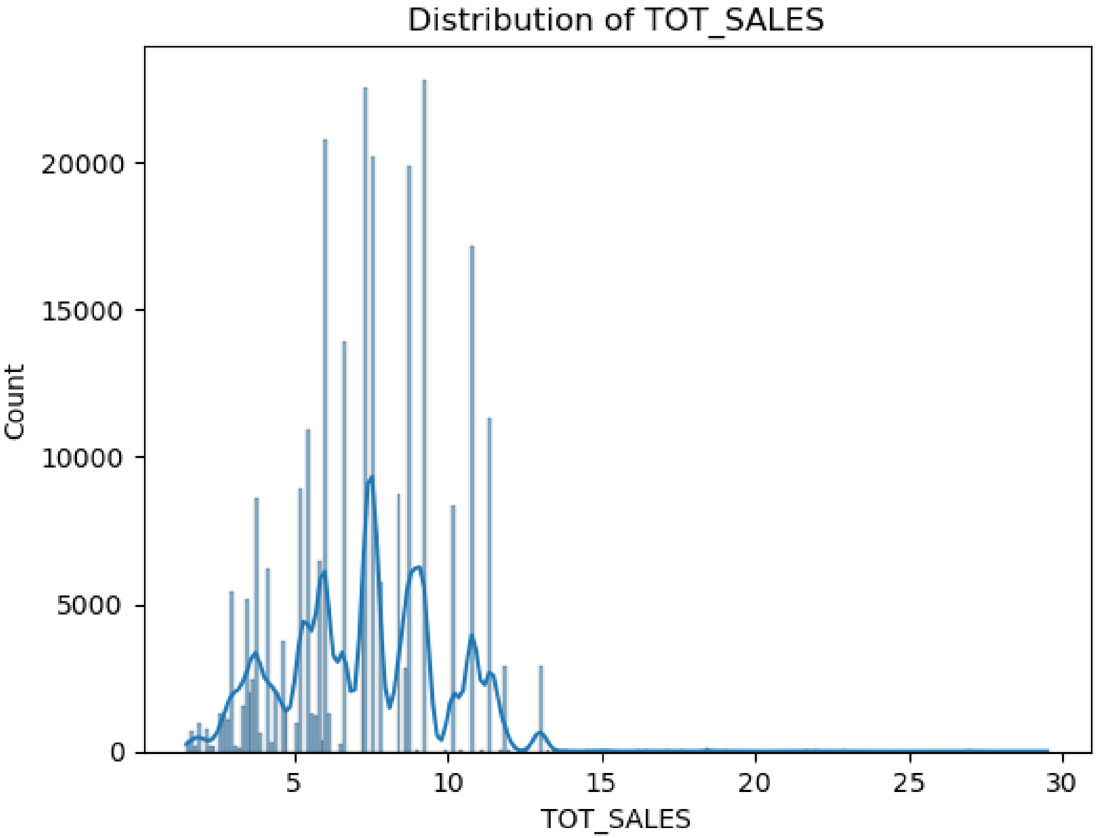
```
sns.histplot(x=df_no_outliers['TOT_SALES'])
plt.show()
```



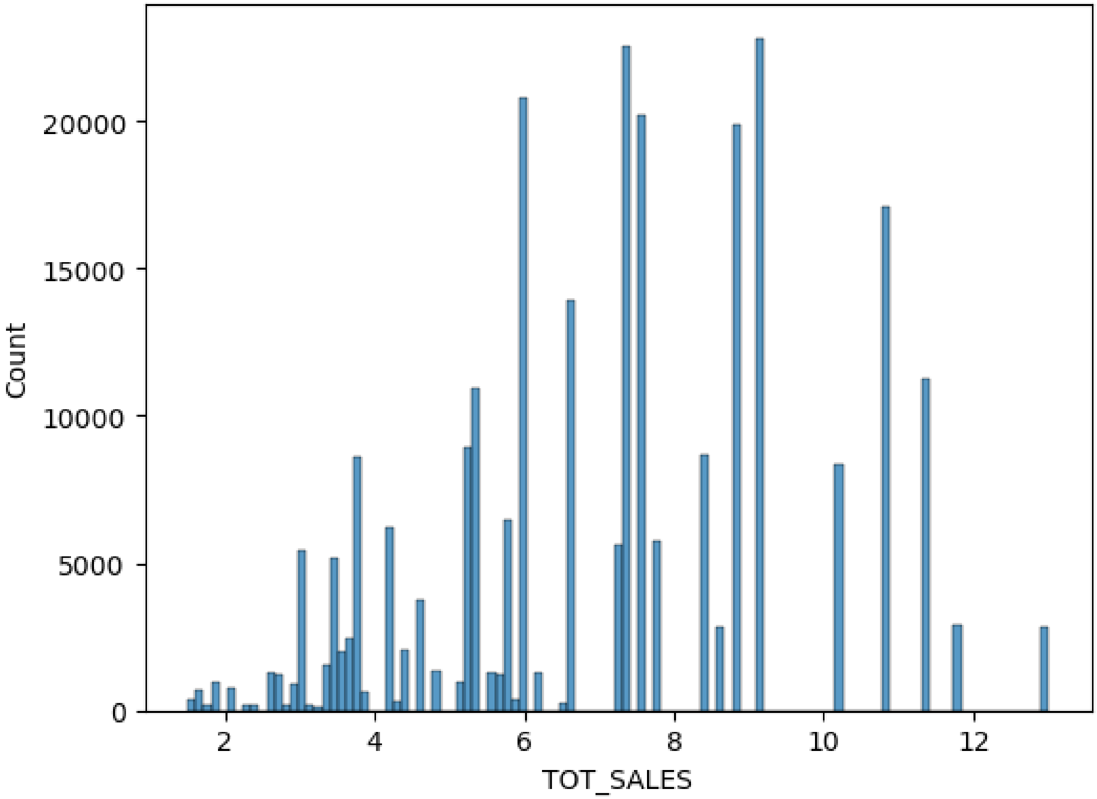
```
Outlier values:
315       4
332       3
523       4
952       5
1012      3
         ..
263285    3
263431    3
263668    3
263830    4
264269    4
Name: PROD_QTY, Length: 1277, dtype: int64
```



Count
200000
150000
100000
50000
0
1.0
1.2
1.4
1.6
1.8
2.0
PROD_QTY



```
Outlier values:
315        7.6
332        6.3
523       10.4
952       15.0
1012      13.8
          …
263285     9.0
263431     8.1
263668    11.7
263830    10.8
264269    21.6
Name: TOT_SALES, Length: 1277, dtype: float64
```



4 Define Metrics

```
[4]: # Total number of customers
total_customers = df['LYLTY_CARD_NBR'].nunique()
print(f"Total number of customers: {total_customers}")
print()

# Average number of transactions per customer
average_transactions_per_customer = df.groupby('LYLTY_CARD_NBR')['TXN_ID'].
  ↪nunique().mean()
print(f"Average number of transactions per customer:␣
  ↪{average_transactions_per_customer:.2f}")
print()

# Total sales revenue
total_sales_revenue = df['TOT_SALES'].sum()
print(f"Total sales revenue: {total_sales_revenue:.2f}")
print()

# Total Spend per Customer
```

```python
total_spend_per_customer = df.groupby('LYLTY_CARD_NBR')['TOT_SALES'].sum()
df['total_spend_per_customer'] = total_spend_per_customer
print("Total Spend per Customer:")
print(total_spend_per_customer)
print()

# Average Spend per Customer
average_spend_per_customer = df.groupby('LYLTY_CARD_NBR')['TOT_SALES'].mean()
df['average_spend_per_customer'] = average_spend_per_customer
print("Average Spend per Customer:")
print(average_spend_per_customer)
print()

# Frequency of Purchase
purchase_frequency = df.groupby('LYLTY_CARD_NBR').size()
df['purchase_frequency'] = purchase_frequency
print("Frequency of Purchase:")
print(purchase_frequency)
print()

# Average Pack Size per Customer
average_pack_size_per_customer = df.groupby('LYLTY_CARD_NBR')['PACK_SIZE'].
 ↪mean()
df['average_pack_size_per_customer'] = average_pack_size_per_customer
print("Average Pack Size per Customer:")
print(average_pack_size_per_customer)
print()
```

```
Total number of customers: 72636

Average number of transactions per customer: 3.62

Total sales revenue: 1933115.00

Total Spend per Customer:
LYLTY_CARD_NBR
1000        6.0
1002        2.7
1003        6.6
1004        1.9
1005        2.8
           …
2370651    13.0
2370701     7.2
2370751     9.2
2370961    18.6
2373711    11.4
Name: TOT_SALES, Length: 72636, dtype: float64
```

```
Average Spend per Customer:
LYLTY_CARD_NBR
1000        6.0
1002        2.7
1003        3.3
1004        1.9
1005        2.8
           …
2370651    13.0
2370701     7.2
2370751     9.2
2370961     9.3
2373711    11.4
Name: TOT_SALES, Length: 72636, dtype: float64

Frequency of Purchase:
LYLTY_CARD_NBR
1000       1
1002       1
1003       2
1004       1
1005       1
          ..
2370651    1
2370701    1
2370751    1
2370961    2
2373711    1
Length: 72636, dtype: int64

Average Pack Size per Customer:
LYLTY_CARD_NBR
1000       175.0
1002       150.0
1003       192.5
1004       160.0
1005       165.0
           …
2370651    380.0
2370701    210.0
2370751    150.0
2370961    232.5
2373711    330.0
Name: PACK_SIZE, Length: 72636, dtype: float64
```

5 Function to calculate the correlation or magnitude distance

[9]:
```
def calculate_distance(trial_store, control_store, measure="correlation"):
    trial_data = df[df['STORE_NBR'] == trial_store]
    control_data = df[df['STORE_NBR'] == control_store]

    if measure == "correlation":
        return np.corrcoef(trial_data['TOT_SALES'],␣
 ↪control_data['TOT_SALES'])[0, 1]
    elif measure == "magnitude_distance":
        observed_distance = np.sum(np.abs(trial_data['TOT_SALES'] -␣
 ↪control_data['TOT_SALES']))
        min_distance = np.sum(np.abs(df['TOT_SALES'] -␣
 ↪control_data['TOT_SALES']))
        max_distance = np.sum(np.abs(df['TOT_SALES'] - df['TOT_SALES']))

        return 1 - (observed_distance - min_distance) / (max_distance -␣
 ↪min_distance)
```

6 Function to find control stores for a given trial store

[8]:
```
def find_control_stores(trial_store, measure="correlation"):
    control_stores = set(df['STORE_NBR'].unique()) - {trial_store}

    distances = [calculate_distance(trial_store, control_store, measure) for␣
 ↪control_store in control_stores]

    selected_control_store = control_stores[np.argmax(distances)]

    return selected_control_store
```

7 Function to calculate a metric for comparing control stores to trial stores

[7]:
```
# Define trial and control stores
trial_stores = [77, 86, 88]
control_stores = [store for store in df['STORE_NBR'].unique() if store not in␣
 ↪trial_stores]

# Function to calculate similarity metric
def calculate_similarity_metric(trial_store, control_store, metric='pearson'):
    trial_data = df[df['STORE_NBR'] == trial_store].select_dtypes(include=np.
 ↪number)
    control_data = df[df['STORE_NBR'] == control_store].
 ↪select_dtypes(include=np.number)
```

```
    if metric == 'pearson':
        similarity_metric = trial_data.corrwith(control_data, axis=0,␣
 ↪numeric_only=True)
    elif metric == 'magnitude_distance':
        # Implement your method for magnitude distance
        pass
    else:
        raise ValueError("Invalid metric. Choose 'pearson' or␣
 ↪'magnitude_distance'")

    return similarity_metric

# Function to select control stores
def select_control_stores(trial_store, control_stores, metric='pearson'):
    similarity_scores = []

    for control_store in control_stores:
        similarity_metric = calculate_similarity_metric(trial_store,␣
 ↪control_store, metric)
        avg_similarity_score = np.mean(similarity_metric)
        similarity_scores.append((control_store, avg_similarity_score))

    sorted_control_stores = sorted(similarity_scores, key=lambda x: x[1],␣
 ↪reverse=True)
    return sorted_control_stores[0][0]

# Function to perform t-test and analyze impact
def analyze_trial_effect(trial_store, control_store):
    trial_data = df[df['STORE_NBR'] == trial_store]
    control_data = df[df['STORE_NBR'] == control_store]

    t_stat, p_value = ttest_ind(trial_data['TOT_SALES'],␣
 ↪control_data['TOT_SALES'])

    if p_value < 0.05:
        print(f"Trial Store {trial_store} has a significant impact on total␣
 ↪sales compared to Control Store {control_store}.")
    else:
        print(f"No significant impact on total sales observed between Trial␣
 ↪Store {trial_store} and Control Store {control_store}.")

# Apply the functions for each trial store
for trial_store in trial_stores:
    selected_control_store = select_control_stores(trial_store, control_stores,␣
 ↪metric='pearson')
```

```
analyze_trial_effect(trial_store, selected_control_store)
```

```
Trial Store 77 has a significant impact on total sales compared to Control Store
1.
Trial Store 86 has a significant impact on total sales compared to Control Store
1.
Trial Store 88 has a significant impact on total sales compared to Control Store
1.
```