Competitive Analysis - MUELLER Brand Performance in the PASTA Category

Student ID：24014297
Name: Ling Leng

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Introduction

1. Introduction

Objective

- Competitive analysis of MUELLER in the PASTA category.
- Use of Dunnhumby Carboload dataset for analysis.

Key Focus Areas

- Evaluate MUELLER's market performance.
- Compare with competitive brands.
- Identify trends in category demand.

Methodology

- SQL data extraction and Python data cleaning.
- Application of the Dirichlet model to set benchmarks.

Outcome

- Actionable insights and strategic recommendations for MUELLER's market growth.

02

Data Preparation & SQL Queries

2. Data Preparation & SQL Queries

Data Source

- Dunnhumby Carboload CSV files
- Dataset: dh_causal_lookup
  dh_product_lookup
  dh_transactions

SQL Data Extraction

- Extracted category data and saved as CSV for further analysis.
- Key steps:
- Import and combine CSV files into SQL database.
- Query data using SQL in jupyter.

Data Cleaning (Python)

- Removed duplicates
- handled missing data
- ensured correct time periods.

```python
# Connecting to a SQLite Database
conn = sqlite3.connect(r'D:\L Leng\master of analytics\156761 Customer␣
↪Insights\A2\A2\Assignment2.db')
```

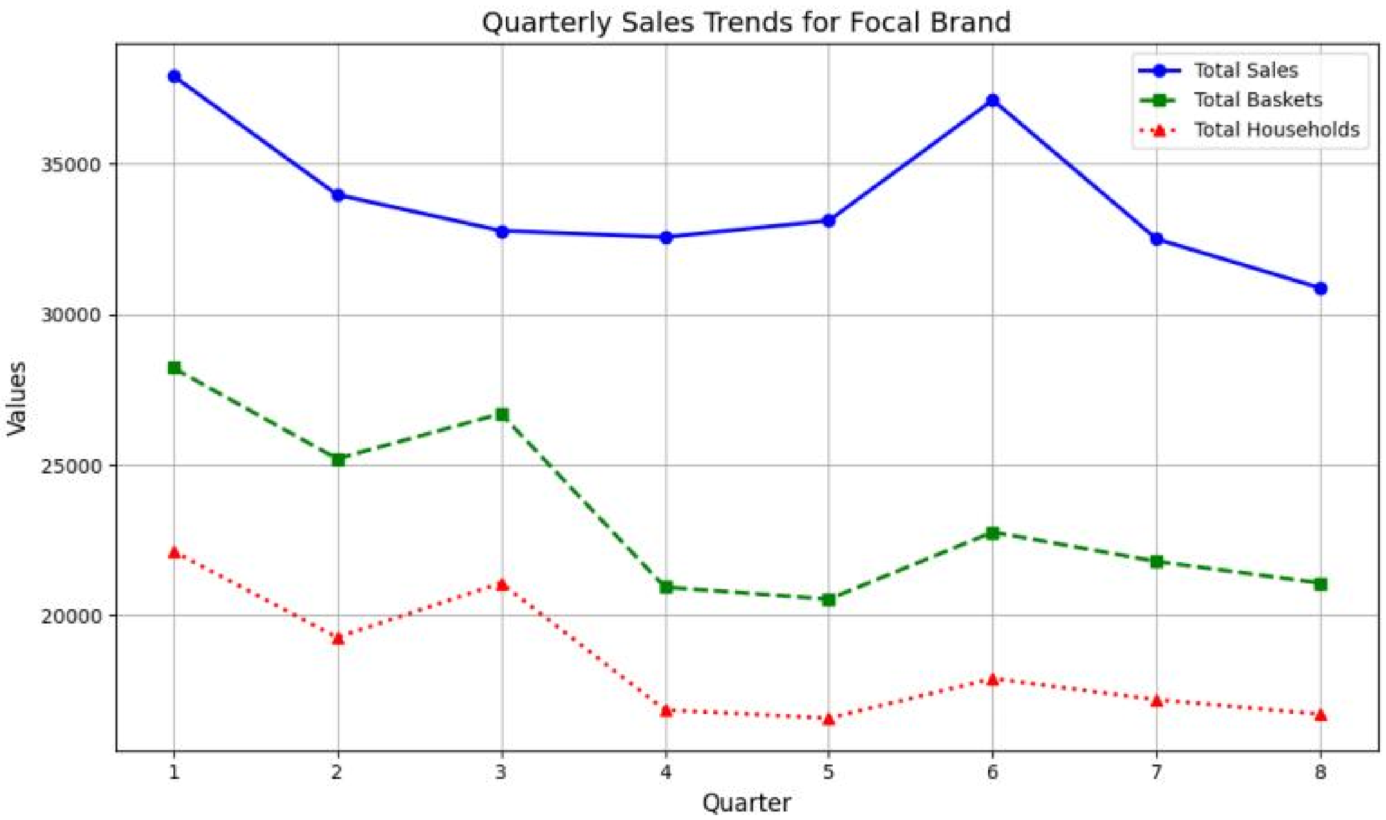
```python
# Perform inner joins to extract related data
query = """
SELECT
    t.upc,
    t.dollar_sales,
    t.units,
    t.time_of_transaction,
    t.week,
    t.household,
    t.basket,
    p.brand,
    p.product_description,
    p.commodity
FROM
    dh_transactions t
JOIN
    dh_product_lookup p
ON
    t.upc = p.upc;
"""
```

03

Brand Performance Analysis: Customer Dashboard

Key Metrics for MUELLER

```
Focal Brand Market Share (B): 9.50%
Focal Brand Purchase Frequency (W): 2.06
```



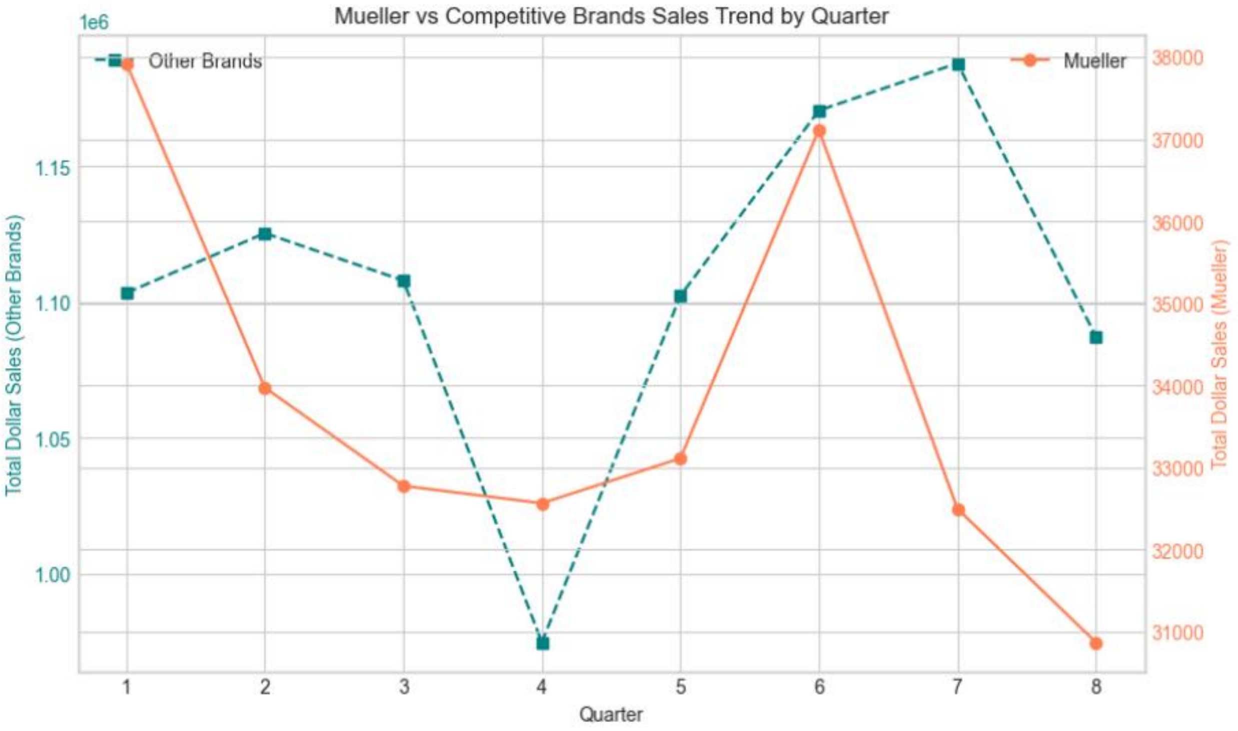
1. [Key Metrics]
- Market Share: 9.50%
- Purchase Frequency: 2.06

2. [Sales Trends]
- Sales Decline: Total sales show a downward trend, with a brief increase in Quarter 6.
- Household Penetration: Gradual decline in households purchasing MUELLER over time.

3. [Insights]
- MUELLER is losing household reach.
- Sales recovery in Quarter 6 is not sustained.

Competitive Comparison

brand	Market_Share_B	Purchase_Frequency_W
Private Label	0.20	1.61
Ragu	0.16	1.47
Prego	0.09	1.41
Aunt Jemima	0.07	1.22
Barilla	0.06	1.32
Classico	0.06	1.27
Private Label Premium	0.05	1.27
Bertolli	0.03	1.24
Ronzoni	0.03	1.25
Creamette	0.03	1.28



1. [Market Share Comparison]

- MUELLER's Market Share: 9.50% (lower compared to leading brands like Private Label at 20%).
- MUELLER's Purchase Frequency: 2.06, which is higher than most competitors, indicating strong loyalty from existing customers.

2. [Sales Trends]

MUELLER vs. Other Brands:

- Other brands consistently outperform MUELLER in total sales.
- MUELLER saw a sales spike in Quarter 6, but it was not sustained, showing a sharp drop in Quarter 8.
- Competitors maintained relatively stable performance compared to MUELLER's fluctuations.

3. [Insights]

- MUELLER's market share is lower than key competitors, but its purchase frequency suggests strong potential to grow.
- The spike in Quarter 6 suggests a temporary successful strategy, but consistency is lacking.

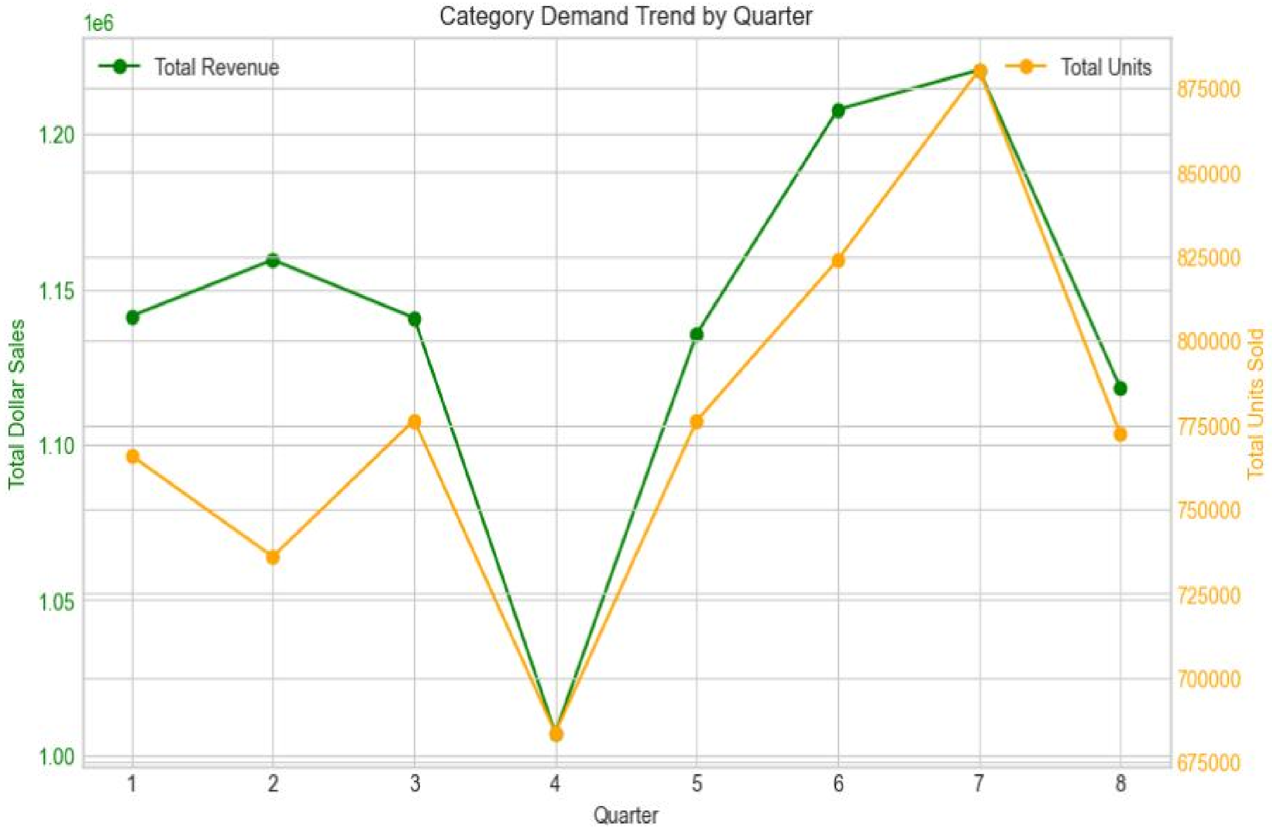
4. [Recommendation]

- Focus on strategies to stabilize sales and increase market share by capturing more customers from competitors like Private Label and Ragu.

Category Demand Trends

Market Share (B): 31.24%

Purchase Frequency (W): 4.76



1. [Key Metrics]

- Market Share: 31.24%

This indicates a significant share in the category, reflecting strong market positioning.

- Purchase Frequency: 4.76

The high purchase frequency suggests strong and frequent demand for the category from consumers.

2. [Demand Trend Insights]

- Total Revenue (Green Line):

There is a notable dip in total revenue in Quarter 4, followed by a sharp increase, peaking in Quarter 6. A decline is observed again in Quarter 8, indicating fluctuations in category demand.

- Total Units Sold (Yellow Line):

Similar to revenue, the number of units sold drops in Quarter 4, then surges in Quarter 6, before another drop in Quarter 8.

3. Conclusion:

- The category shows overall strong demand but with significant seasonal fluctuations.
- The spike in Quarter 6 suggests the category may be influenced by promotions or seasonal factors.

4. Recommendation:

Implement targeted marketing during low-demand periods (such as Quarters 4 and 8) to stabilize sales throughout the year.

04

Dirichlet Model Insights

1. Model Fit and Validation

TABLE 2
Model Fitting Statistics

								Intermediary				Model Fitting Calculations				
Brand	b	w	Mkt Share	Use to Est	s^	weighted s^	p0	m	m/M	weight	b	w	|b|	|w|		
Mueller	0.1	2.1			3.987		91%	0.2	13%		-0.02	0.39	0.02	0.39	23%	19%
Private Label	0.0	1.6		Y	4.942	.1	98%	0.0	2%	0.02	-0.01	0.41	0.01	0.41	35%	26%
Ragu	0.2	1.5		Y	50.001	7.9	84%	0.2	16%	0.16	0.03	-0.31	0.03	0.31	17%	21%
Prego	0.1	1.4		Y	50.001	4.3	91%	0.1	9%	0.09	0.00	-0.07	0.00	0.07	4%	5%
Aunt Jemima	0.1	1.2		Y	50.001	2.9	93%	0.1	6%	0.06	0.01	-0.14	0.01	0.14	10%	11%
Barilla	0.1	1.3		Y	48.503	2.6	94%	0.1	5%	0.05	0.00	-0.02	0.00	0.02	1%	1%
Classico	0.1	1.3		Y	50.001	2.6	94%	0.1	5%	0.05	0.00	-0.06	0.00	0.06	4%	5%
Private Label Premi	0.1	1.3		Y	49.499	2.1	95%	0.1	4%	0.04	0.00	-0.02	0.00	0.02	2%	2%
Bertolli	0.0	1.2		Y	26.974	.7	97%	0.0	3%	0.03	0.00	0.03	0.00	0.03	2%	2%
Ronzoni	0.0	1.3		Y	25.022	.6	97%	0.0	3%	0.03	0.00	0.04	0.00	0.04	3%	3%
Creamette	0.0	1.3		Y	20.431	.5	97%	0.0	3%	0.03	0.00	0.06	0.00	0.06	5%	5%

- The **Dirichlet model** was applied to validate MUELLER's market performance metrics, including **market share** and **purchase frequency**. The model's penetration rate and purchase frequency predictions were a good match with actual data, confirming that the brand is performing as expected.

- **MUELLER**'s market share (**10%**) and purchase frequency (**2.1**) align closely with the model estimates, showing that the brand is attracting repeat buyers but has room to improve its overall penetration.

2. Penetration and Market Share

TABLE 1 Output Statistics	Brand Share	Penetration O	T	% Buying Once T	Five + T	Purchases Per Buyer of the Brand O	T	of the Category T	Share of Category Requirements T	100% Loyal % T	Rate T	Repeat Buying T
1 Mueller		10%	12%	64%	4%	2.1	1.7	8.1	21%	12%	1.1	51%
2 Private Label		2%	3%	85%	0%	1.6	1.2	10.1	12%	8%	1.0	25%
3 Ragu		16%	13%	61%	5%	1.5	1.8	7.7	23%	13%	1.1	54%
4 Prego		9%	9%	71%	2%	1.4	1.5	8.8	17%	11%	1.1	43%
5 Aunt Jemima		7%	6%	76%	1%	1.2	1.4	9.3	15%	10%	1.0	37%
6 Barilla		6%	6%	77%	1%	1.3	1.3	9.4	14%	9%	1.0	36%
7 Classico		6%	6%	77%	1%	1.3	1.3	9.4	14%	9%	1.0	35%
8 Private Label Premium		5%	5%	79%	1%	1.3	1.3	9.6	13%	9%	1.0	33%
9 Bertolli		3%	3%	84%	0%	1.2	1.2	10.0	12%	8%	1.0	27%
10 Ronzoni		3%	3%	84%	0%	1.3	1.2	10.0	12%	8%	1.0	27%
11 Creamette		3%	3%	84%	0%	1.3	1.2	10.0	12%	8%	1.0	27%

- **MUELLER** has a **12% penetration rate**, which is lower than **Private Label (16%)** and **Ragu (13%)**. The model results suggest that while MUELLER is capturing a loyal customer base, it needs to focus on expanding its reach to more households.

- Other competing brands like **Private Label** and **Ragu** hold higher penetration rates and market share, indicating that MUELLER is lagging in terms of broad consumer adoption.

3. Repeat Purchase and Loyalty

TABLE 1 Output Statistics	Brand Share	Penetration	% Buying Once	% Buying Five +	Purchases Per Buyer of the Brand		Purchases Per Buyer of the Category	Share of Category Requirements	100% Loyal %	100% Loyal Rate	Repeat Buying
1 Mueller	10%	12%	64%	4%	2.1	1.7	8.1	21%	12%	1.1	51%
2 Private Label	2%	3%	85%	0%	1.6	1.2	10.1	12%	8%	1.0	25%
3 Ragu	16%	13%	61%	5%	1.5	1.8	7.7	23%	13%	1.1	54%
4 Prego	9%	9%	71%	2%	1.4	1.5	8.8	17%	11%	1.1	43%
5 Aunt Jemima	7%	6%	76%	1%	1.2	1.4	9.3	15%	10%	1.0	37%
6 Barilla	6%	6%	77%	1%	1.3	1.3	9.4	14%	9%	1.0	36%
7 Classico	6%	6%	77%	1%	1.3	1.3	9.4	14%	9%	1.0	35%
8 Private Label Premium	5%	5%	79%	1%	1.3	1.3	9.6	13%	9%	1.0	33%
9 Bertolli	3%	3%	84%	0%	1.2	1.2	10.0	12%	8%	1.0	27%
10 Ronzoni	3%	3%	84%	0%	1.3	1.2	10.0	12%	8%	1.0	27%
11 Creamette	3%	3%	84%	0%	1.3	1.2	10.0	12%	8%	1.0	27%

- **MUELLER's repeat purchase rate** is **51%**, which is higher than competitors such as **Private Label (25%)** and **Prego (43%)**. This shows that MUELLER has strong customer loyalty, but the lower penetration limits the brand's overall market potential.

- Increasing the penetration rate without sacrificing the loyalty of existing customers should be a key strategy for growth.

4. Model Accuracy

Model Fitting Statistics							
K	.162		A	9.2		s^	44.42
Penetration				Purchases Per Buyer			
AVE%	1.6%	✓		AVE%	2.1%	✓	
.r	0.96	✓		.r	0.58	×	
MAD%	10.8%	✓		MAD%	10.0%	✓	
MAPE	9.8%	✓		MAPE	9.0%	✓	
Number of Tests Passed				7	out of	8	

- The model's **MAD% (Mean Absolute Deviation)** and **MAPE (Mean Absolute Percentage Error)** values are low, with MAD% for penetration at **10.8%** and for purchases per buyer at **10.0%**, confirming that the model provides an accurate fit.

- The MAPE values also demonstrate the model's predictive strength, as they remain under **10%**, a strong indicator that the Dirichlet model can reliably estimate market dynamics in the PASTA category.

5. Competitor Analysis

TABLE 1 Output Statistics	Brand Share	Penetration	% Buying		Purchases Per Buyer		Share of Category	100% Loyal		Repeat Buying	
			Once	Five +	of the Brand	of the Category	Requirements	%	Rate		
1 Mueller	10%	12%	64%	4%	2.1	1.7	8.1	21%	12%	1.1	51%
2 Private Label	2%	3%	85%	0%	1.6	1.2	10.1	12%	8%	1.0	25%
3 Ragu	16%	13%	61%	5%	1.5	1.8	7.7	23%	13%	1.1	54%
4 Prego	9%	9%	71%	2%	1.4	1.5	8.8	17%	11%	1.1	43%
5 Aunt Jemima	7%	6%	76%	1%	1.2	1.4	9.3	15%	10%	1.0	37%
6 Barilla	6%	6%	77%	1%	1.3	1.3	9.4	14%	9%	1.0	36%
7 Classico	6%	6%	77%	1%	1.3	1.3	9.4	14%	9%	1.0	35%
8 Private Label Premium	5%	5%	79%	1%	1.3	1.3	9.6	13%	9%	1.0	33%
9 Bertolli	3%	3%	84%	0%	1.2	1.2	10.0	12%	8%	1.0	27%
10 Ronzoni	3%	3%	84%	0%	1.3	1.2	10.0	12%	8%	1.0	27%
11 Creamette	3%	3%	84%	0%	1.3	1.2	10.0	12%	8%	1.0	27%

- **Private Label** leads the category with a **20% market share** and a **16% penetration rate**, making it the dominant player in the PASTA category.

- **MUELLER** has a relatively low **10% market share**, but its higher purchase frequency and repeat purchase rate (51%) show the potential for growth if the brand can increase household reach.

- Competing brands like **Ragu (13% penetration, 16% market share)** and **Prego (9% penetration, 9% market share)** provide a middle ground, showing that these brands also balance moderate penetration with loyal customers.

6. Recommendations for MUELLER

- **Increase Penetration**: MUELLER should focus on expanding its customer base by investing in targeted marketing campaigns to attract new buyers. Increasing penetration is key to capturing more market share.

- **Leverage Loyalty**: The high loyalty rate indicates an opportunity to capitalize on repeat customers through loyalty programs or bundled offers to further increase purchase frequency.

- **Competitive Strategy**: Given that Private Label dominates with a significantly higher market share, MUELLER could differentiate itself by emphasizing product quality or sustainability to appeal to more discerning buyers.

05

Conclusion and Recommendations

1. [Conclusion]

- **MUELLER** is performing well in terms of customer loyalty, with a **51% repeat purchase rate** and a **purchase frequency of 2.1**. However, its **market share (10%)** and **penetration (12%)** are lower than key competitors like **Private Label** and **Ragu**.
- The **Dirichlet model** confirms that MUELLER's current performance aligns with theoretical expectations, indicating a solid customer base but with room for expansion.

2. [Recommendations]

- **Increase Market Penetration**: MUELLER should focus on expanding its reach to new households through targeted marketing campaigns and promotions. This will help boost its low penetration rate.
- **Enhance Brand Awareness**: Marketing efforts should emphasize MUELLER's product quality and value, positioning it as a preferred brand in the **PASTA** category to compete with market leaders.
- **Leverage Customer Loyalty**: With a high repeat purchase rate, MUELLER can introduce loyalty programs or bundled offers to incentivize more frequent purchases from existing customers and retain them long-term.

Thanks for watching

156762_Customer Insights_Assignment2

September 18, 2024

[1]:
```python
import sqlite3
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import scipy.stats as stats
```

1 Write an SQL query to extract and save a .csv file containing relevant category data

[2]:
```python
# Connecting to a SQLite Database
conn = sqlite3.connect(r'D:\L Leng\master of analytics\156761 Customer␣
↪Insights\A2\A2\Assignment2.db')
```

[3]:
```python
# Query all table names in the database
tables_query = "SELECT name FROM sqlite_master WHERE type='table';"
tables = conn.execute(tables_query).fetchall()

for table in tables:
    print(table[0])
```

```
dh_causal_lookup
dh_product_lookup
dh_transactions
```

[4]:
```python
# 1. View the field information of dh_causal_lookup
table_name = 'dh_causal_lookup'
columns_query = f"PRAGMA table_info({table_name});"
columns = conn.execute(columns_query).fetchall()

for column in columns:
    print(f"Column ID: {column[0]}, Name: {column[1]}, Type: {column[2]}")

# 2. View the field information of dh_product_lookup
```

```python
table_name = 'dh_product_lookup'
columns_query = f"PRAGMA table_info({table_name});"
columns = conn.execute(columns_query).fetchall()

for column in columns:
    print(f"Column ID: {column[0]}, Name: {column[1]}, Type: {column[2]}")

# 3. View the field information of dh_transactions
table_name = 'dh_transactions'
columns_query = f"PRAGMA table_info({table_name});"
columns = conn.execute(columns_query).fetchall()

for column in columns:
    print(f"Column ID: {column[0]}, Name: {column[1]}, Type: {column[2]}")
```

```
Column ID: 0, Name: upc, Type: REAL
Column ID: 1, Name: store, Type: INTEGER
Column ID: 2, Name: week, Type: INTEGER
Column ID: 3, Name: feature_desc, Type: TEXT
Column ID: 4, Name: display_desc, Type: TEXT
Column ID: 5, Name: geography, Type: INTEGER
Column ID: 0, Name: upc, Type: INTEGER
Column ID: 1, Name: product_description, Type: TEXT
Column ID: 2, Name: commodity, Type: TEXT
Column ID: 3, Name: brand, Type: TEXT
Column ID: 4, Name: product_size, Type: TEXT
Column ID: 0, Name: upc, Type: INTEGER
Column ID: 1, Name: dollar_sales, Type: REAL
Column ID: 2, Name: units, Type: INTEGER
Column ID: 3, Name: time_of_transaction, Type: INTEGER
Column ID: 4, Name: geography, Type: INTEGER
Column ID: 5, Name: week, Type: INTEGER
Column ID: 6, Name: household, Type: INTEGER
Column ID: 7, Name: store, Type: INTEGER
Column ID: 8, Name: basket, Type: INTEGER
Column ID: 9, Name: day, Type: INTEGER
Column ID: 10, Name: coupon, Type: INTEGER
```

[7]:
```python
# Perform inner joins to extract related data
query = """
SELECT
    t.upc,
    t.dollar_sales,
    t.units,
    t.time_of_transaction,
    t.week,
    t.household,
```

```
    t.basket,
    p.brand,
    p.product_description,
    p.commodity
FROM
    dh_transactions t
JOIN
    dh_product_lookup p
ON
    t.upc = p.upc;
"""
```

[8]:
```
# Execute the query and save the results as a pandas DataFrame
df = pd.read_sql_query(query, conn)
```

[9]:
```
# Export query results to a CSV file
df.to_csv('relevant_category_data.csv', index=False)
```

2 Use Python and Jupyter notebooks to clean the data

[3]:
```
# Reload data from a CSV file
df = pd.read_csv('relevant_category_data.csv')

print(df.head())
```

```
          upc  dollar_sales  units  time_of_transaction  week  household  \
0  7680850106          0.80      1                 1100     1     125434
1  3620000470          3.59      1                 1100     1     125434
2  1800028064          2.25      1                 1137     1     108320
3  9999985067          0.85      1                 1148     1     162016
4  9999985131          2.19      1                 1323     1      89437

   basket                 brand             product_description  \
0       1               Barilla               BARILLA ANGEL HAIR
1       1              Bertolli        BERTOLLI TOM&BASIL SAUCE
2       2           Hungry Jack       H J PANCK BTRMLK COMP MIX
3       3         Private Label        PRIVATE LABEL VERMICELLI
4       4 Private Label Premium  PRIVATE LABEL IMPORTED LASAGNA

       commodity
0          pasta
1    pasta sauce
2  pancake mixes
3          pasta
4          pasta
```

2.1 1. Check for missing and duplicate values

[4]:
```python
# Check if there are any missing values
missing_values = df.isnull().sum()
print("Missing value statistics:\n", missing_values)

# Remove Duplicate Rows
df = df.drop_duplicates()
```

```
Missing value statistics:
 upc                    0
dollar_sales           0
units                  0
time_of_transaction    0
week                   0
household              0
basket                 0
brand                  0
product_description    0
commodity              0
dtype: int64
```

2.2 2. Time column processing

[5]:
```python
# Make sure 'time_of_transaction' is in date format
df['time_of_transaction'] = pd.to_datetime(df['time_of_transaction'],␣
↪errors='coerce')

# Check if there are any invalid dates or dates that failed conversion
invalid_dates = df[df['time_of_transaction'].isnull()]
print("Invalid date entry:\n", invalid_dates)
```

```
Invalid date entry:
 Empty DataFrame
Columns: [upc, dollar_sales, units, time_of_transaction, week, household,
basket, brand, product_description, commodity]
Index: []
```

[6]:
```python
# Check data volume by week
weekly_counts = df['week'].value_counts().sort_index()
print("Trading volume by week:\n", weekly_counts)
```

```
Trading volume by week:
 1      43148
2      45735
3      54344
```

```
4       53512
5       43824
        ...
100     47815
101     50571
102     47365
103     49884
104     53626
Name: week, Length: 104, dtype: int64
```

[7]:
```
# Delete data with incomplete time periods
df_cleaned = df.dropna(subset=['time_of_transaction', 'week'])
```

[8]:
```
# Check the cleaned data
print(df_cleaned.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5197681 entries, 0 to 5197680
Data columns (total 10 columns):
 #   Column               Dtype
---  ------               -----
 0   upc                  int64
 1   dollar_sales         float64
 2   units                int64
 3   time_of_transaction  datetime64[ns]
 4   week                 int64
 5   household            int64
 6   basket               int64
 7   brand                object
 8   product_description  object
 9   commodity            object
dtypes: datetime64[ns](1), float64(1), int64(5), object(3)
memory usage: 436.2+ MB
None
```

2.3 3. Filter outliers

[9]:
```
# Set pandas not to use scientific notation
pd.set_option('display.float_format', '{:.2f}'.format)

# Re-examine the descriptive statistics
print(df.describe())
```

```
                 upc  dollar_sales      units       week  household     basket
count     5197681.00    5197681.00 5197681.00 5197681.00 5197681.00 5197681.00
mean   6203548088.76          1.76       1.20      53.22  223137.62 1662961.43
std    3152023380.33          1.13       0.57      30.05  141216.42  959318.89
min     111112360.00        -11.76       1.00       1.00       1.00       1.00
```

```
25%    3620000300.00          0.99        1.00       27.00    99053.00  829906.00
50%    5100012910.00          1.50        1.00       55.00   209694.00 1666884.00
75%    9999981583.00          2.19        1.00       79.00   339568.00 2496495.00
max    9999985766.00        153.14      156.00      104.00   510027.00 3316349.00
```

[10]:
```python
# Delete records with negative sales
df_cleaned = df[df['dollar_sales'] >= 0]

# Check the cleaned data
print(df_cleaned.describe())

# Reassign the cleaned data to df
df = df_cleaned
```

```
                 upc  dollar_sales       units        week   household     basket
count     5193177.00    5193177.00  5193177.00  5193177.00  5193177.00 5193177.00
mean   6204517447.02          1.76        1.20       53.23   223121.95 1663045.33
std    3152341097.98          1.13        0.57       30.05   141227.64  959354.44
min     111112360.00          0.00        1.00        1.00        1.00       1.00
25%    3620000300.00          0.99        1.00       27.00    99006.00  830008.00
50%    5100012910.00          1.50        1.00       55.00   209669.00 1666846.00
75%    9999981583.00          2.19        1.00       79.00   339573.00 2496690.00
max    9999985766.00        153.14      156.00      104.00   510027.00 3316349.00
```

3 Creating Customer Dashboard and Visualization

3.1 1. Customer Dashboard

3.1.1 1. 1 customer dashboard for the focal brand(MUELLER)

[11]:
```python
# Generates the 'Quarter' column for every 13 weeks in a quarter
df['Quarter'] = (df['week'] - 1) // 13 + 1

print(df[['week', 'Quarter']].head())
```

```
   week  Quarter
0     1        1
1     1        1
2     1        1
3     1        1
4     1        1
```

[12]:
```python
# Filter out the data of focal brand -- 'Mueller'
focal_brand = 'Mueller'
df_focal = df[df['brand'] == focal_brand]

# Summary of focal brand key indicators by quarter
```

```
focal_metrics = df_focal.groupby('Quarter').agg(
    Total_Revenue=('dollar_sales', 'sum'),
    Total_Units=('units', 'sum'),
    Total_SKUs=('upc', 'nunique'),
    Total_Baskets=('basket', 'nunique'),
    Total_Households=('household', 'nunique')
)

print(focal_metrics)
```

```
         Total_Revenue  Total_Units  Total_SKUs  Total_Baskets  \
Quarter
1             37925.61        47181          25          28223
2             33974.97        31650          24          25205
3             32778.68        39601          27          26702
4             32567.47        25324          25          20941
5             33114.07        25351          24          20540
6             37116.89        27743          23          22769
7             32499.61        26719          21          21793
8             30873.20        25830          21          21074

         Total_Households
Quarter
1                   22140
2                   19270
3                   21078
4                   16863
5                   16589
6                   17903
7                   17202
8                   16719
```

3.1.2 1.2 customer dashboard for the Competitive Performance

[13]:
```
# Aggregate sales and purchase data for all brands in different quarters, by␣
↪brand and quarter
competitive_metrics = df.groupby(['Quarter', 'brand']).agg(
    Total_Revenue=('dollar_sales', 'sum'),
    Total_Units=('units', 'sum'),
    Total_Baskets=('basket', 'nunique'),
    Total_Households=('household', 'nunique')
).reset_index()

# Exclude the 'Mueller' brand and sort the brands by total sales
top_10_brands = competitive_metrics[competitive_metrics['brand'] != 'Mueller'].
↪groupby('brand').agg(
    Total_Revenue=('Total_Revenue', 'sum')
```

```
).reset_index().sort_values(by='Total_Revenue', ascending=False).head(10)

# Get data on the top 10 brands
top_10_metrics = competitive_metrics[competitive_metrics['brand'].
 ↪isin(top_10_brands['brand'])]
print(top_10_metrics)
```

```
     Quarter                 brand  Total_Revenue  Total_Units  \
6          1           Aunt Jemima       72361.99        28130
7          1               Barilla       69294.24        48762
9          1              Bertolli       27095.80         9554
20         1              Classico       60181.43        24752
24         1             Creamette       37091.72        35557
..       ...                   ...            ...          ...
756        8                Hunt's       28833.15        32423
786        8                Prego        92435.64        45327
787        8         Private Label      216700.10       255201
788        8 Private Label Premium       50300.09        34400
791        8                  Ragu      176330.57       100928

     Total_Baskets  Total_Households
6            25377             20666
7            33267             25189
9             7905              6308
20           17613             13526
24           28189             21781
..             ...               ...
756          19410             14680
786          33534             23702
787         157610             98115
788          25404             19942
791          74320             50409

[80 rows x 6 columns]
```

3.1.3 1.3 customer dashboard for the Category Demand Trends

[14]:
```
# Aggregate sales and purchase data for the entire category in different␣
 ↪quarters
category_metrics = df.groupby('Quarter').agg(
    Total_Category_Revenue=('dollar_sales', 'sum'),
    Total_Category_Units=('units', 'sum'),
    Total_Category_Baskets=('basket', 'nunique'),
    Total_Category_Households=('household', 'nunique')
)

print(category_metrics)
```

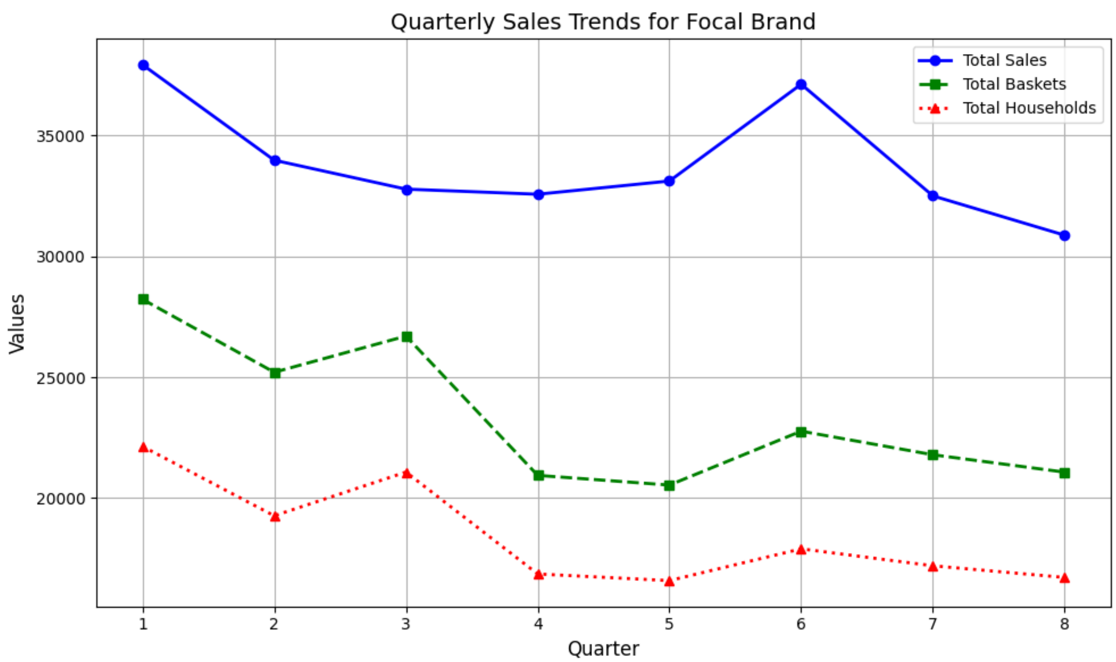
```
        Total_Category_Revenue  Total_Category_Units  Total_Category_Baskets  \
Quarter
1                   1141361.63                765849                  404337
2                   1159413.84                735915                  418127
3                   1140770.75                776400                  414608
4                   1007255.96                683649                  368721
5                   1135519.88                776148                  413475
6                   1207767.57                823988                  446374
7                   1220550.05                880329                  446205
8                   1118279.40                772252                  403685

        Total_Category_Households
Quarter
1                          190704
2                          197483
3                          195335
4                          181891
5                          197181
6                          208475
7                          207332
8                          195558
```

3.2 2. Visualization

3.2.1 2.1 Quarterly sales trends for Focal Brand

[15]:
```
# Summarize the quarterly sales data of focal brand and add the summaries of␣
↪basket and household
focal_sales_by_quarter = df_focal.groupby('Quarter').agg(
    Total_Sales=('dollar_sales', 'sum'),
    Total_Baskets=('basket', 'nunique'),
    Total_Households=('household', 'nunique')
)

plt.figure(figsize=(10, 6))

# Draw a line chart of sales
plt.plot(focal_sales_by_quarter.index, focal_sales_by_quarter['Total_Sales'],
         marker='o', linestyle='-', color='blue', linewidth=2, label='Total␣
↪Sales')

# Plot a trend graph for baskets and households
plt.plot(focal_sales_by_quarter.index, focal_sales_by_quarter['Total_Baskets'],
         marker='s', linestyle='--', color='green', linewidth=2, label='Total␣
↪Baskets')
plt.plot(focal_sales_by_quarter.index,␣
↪focal_sales_by_quarter['Total_Households'],
```

```
        marker='^', linestyle=':', color='red', linewidth=2, label='Total␣
↪Households')

plt.title('Quarterly Sales Trends for Focal Brand', fontsize=14)
plt.xlabel('Quarter', fontsize=12)
plt.ylabel('Values', fontsize=12)
plt.legend()
plt.grid(True)
plt.xticks(focal_sales_by_quarter.index)
plt.tight_layout()
plt.show()
```

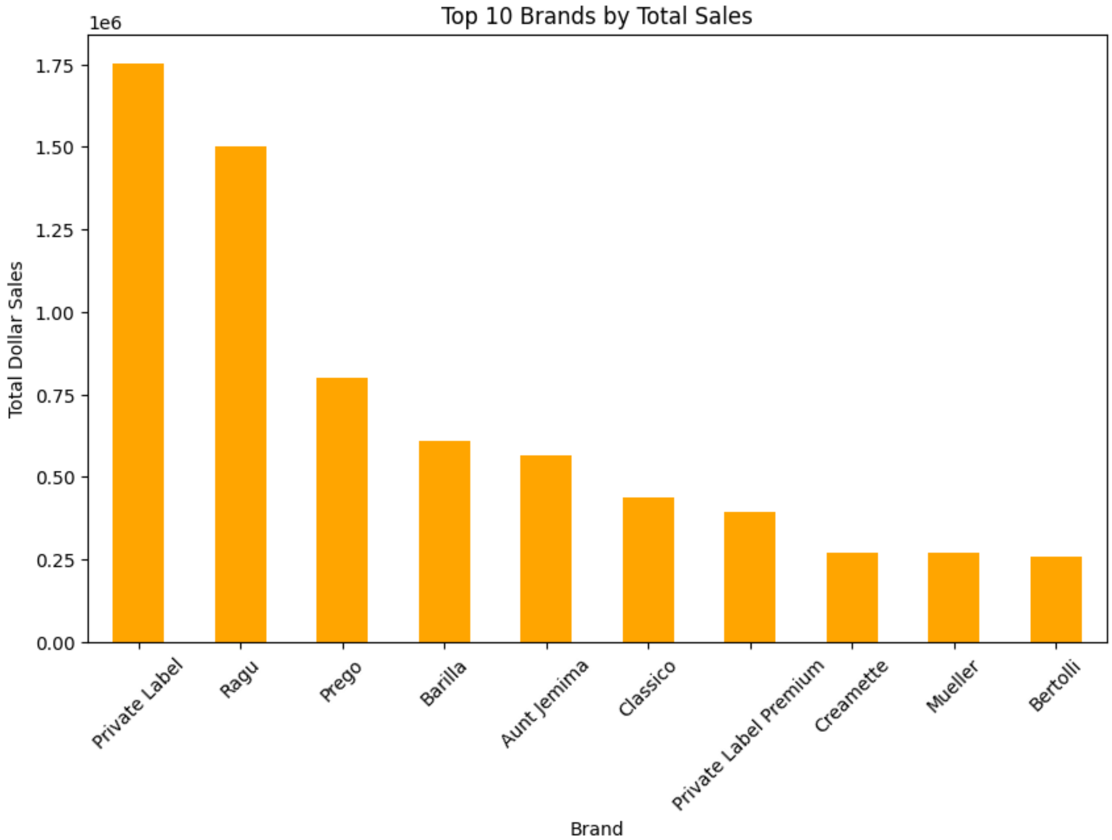


3.2.2 2.2 Comparison of performance of competing brands

2.2.1 Comparison of sales of the top 10 brands

[16]:
```
# Calculate total sales for all brands
brand_sales = df.groupby('brand')['dollar_sales'].sum().
↪sort_values(ascending=False)

# Select the top 10 brands for analysis
top_brands = brand_sales.head(10)

# Draw a bar chart of sales of the top 10 brands
plt.figure(figsize=(10,6))
top_brands.plot(kind='bar', color='orange')
```

```
plt.title('Top 10 Brands by Total Sales')
plt.xlabel('Brand')
plt.ylabel('Total Dollar Sales')
plt.xticks(rotation=45)
plt.show()
```



2.2.2 Compare focal brand to competing brands

[17]:
```
# Check the sales summary of focal brand Mueller
focal_sales = df_focal.groupby('Quarter')['dollar_sales'].sum()
print(focal_sales)
```

```
Quarter
1    37925.61
2    33974.97
3    32778.68
4    32567.47
5    33114.07
6    37116.89
7    32499.61
```

```
8    30873.20
Name: dollar_sales, dtype: float64
```

[18]:

```
# Calculate the quarterly sales of competing brands
competitive_sales = df[df['brand'] != focal_brand].
 ↪groupby('Quarter')['dollar_sales'].sum()

plt.style.use('seaborn-whitegrid')
fig, ax1 = plt.subplots(figsize=(10,6))

# Plotting the quarterly sales trends of competing brands (left axis)
ax1.plot(competitive_sales.index, competitive_sales.values, marker='s',␣
 ↪linestyle='--', color='teal', label='Other Brands')
ax1.set_xlabel('Quarter')
ax1.set_ylabel('Total Dollar Sales (Other Brands)', color='teal')
ax1.tick_params(axis='y', labelcolor='teal')

# Plotting Mueller's quarterly sales trend (right axis)
ax2 = ax1.twinx()
ax2.plot(focal_sales.index, focal_sales.values, marker='o', linestyle='-',␣
 ↪color='coral', label='Mueller')
ax2.set_ylabel('Total Dollar Sales (Mueller)', color='coral')
ax2.tick_params(axis='y', labelcolor='coral')

ax1.legend(loc='upper left')
ax2.legend(loc='upper right')

plt.title('Mueller vs Competitive Brands Sales Trend by Quarter')
plt.show()
```

```
C:\Users\23968\AppData\Local\Temp\ipykernel_7344\478139940.py:5:
MatplotlibDeprecationWarning: The seaborn styles shipped by Matplotlib are
deprecated since 3.6, as they no longer correspond to the styles shipped by
seaborn. However, they will remain available as 'seaborn-v0_8-<style>'.
Alternatively, directly use the seaborn API instead.
  plt.style.use('seaborn-whitegrid')
```

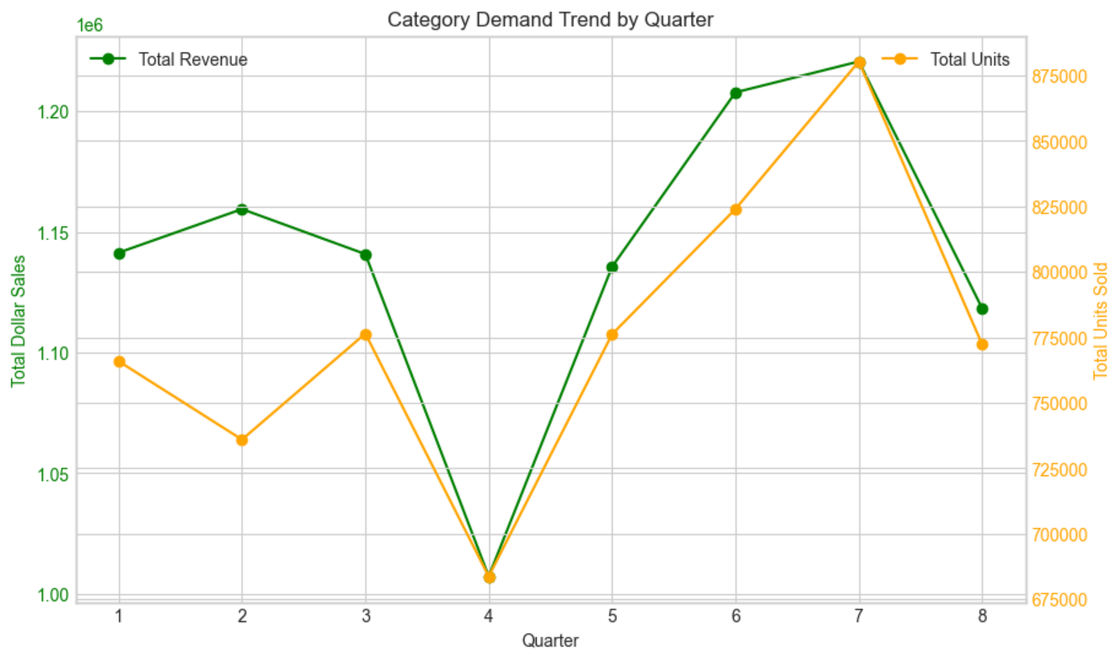
2.2.3 Charting Category Demand Trends

[19]:
```
# Summarize sales and purchases for the entire category by quarter and keep␣
↪'Quarter'
category_metrics = df.groupby('Quarter').agg(
    Total_Category_Revenue=('dollar_sales', 'sum'),
    Total_Category_Units=('units', 'sum')
).reset_index()

print(category_metrics.columns)
```

```
Index(['Quarter', 'Total_Category_Revenue', 'Total_Category_Units'],
dtype='object')
```

[20]:
```
# Redraw the chart
fig, ax1 = plt.subplots(figsize=(10,6))

# Plotting total sales trends by category
ax1.plot(category_metrics['Quarter'],␣
↪category_metrics['Total_Category_Revenue'], marker='o', color='green',␣
↪label='Total Revenue')
ax1.set_xlabel('Quarter')
ax1.set_ylabel('Total Dollar Sales', color='green')
ax1.tick_params(axis='y', labelcolor='green')
```

```
# Using the shared x-axis of ax1, plot the trend of total purchases by category
ax2 = ax1.twinx()
ax2.plot(category_metrics['Quarter'], category_metrics['Total_Category_Units'],␣
 ↪marker='o', color='orange', label='Total Units')
ax2.set_ylabel('Total Units Sold', color='orange')
ax2.tick_params(axis='y', labelcolor='orange')

ax1.legend(loc='upper left')
ax2.legend(loc='upper right')

plt.title('Category Demand Trend by Quarter')
plt.grid(True)
plt.show()
```



4 Calculate the relevant data required for the Dirichlet spreadsheet

4.1 1. Calculate category data

[21]:
```
# Filter out data for the Pasta category
df_pasta = df[df['commodity'] == 'pasta']

# Calculate the total sales, total number of orders, and total number of␣
 ↪households in the Pasta category
total_revenue_pasta = df_pasta['dollar_sales'].sum()
total_baskets_pasta = df_pasta['basket'].nunique()
```

```
total_households_pasta = df_pasta['household'].nunique()

# Assume total_market_revenue is the total market revenue
total_market_revenue = df['dollar_sales'].sum()

# Calculate Market Share (B)
market_share_B = total_revenue_pasta / total_market_revenue
print(f"Market Share (B): {market_share_B:.2%}")

# Calculate Purchase Frequency (W)
purchase_frequency_W = total_baskets_pasta / total_households_pasta
print(f"Purchase Frequency (W): {purchase_frequency_W:.2f}")
```

```
Market Share (B): 31.24%
Purchase Frequency (W): 4.76
```

4.2 2. Calculate data of focal brand

[22]:
```
focal_brand = 'Mueller'
df_focal = df[df['brand'] == focal_brand]

total_revenue_focal = df_focal['dollar_sales'].sum()
total_baskets_focal = df_focal['basket'].nunique()
total_households_focal = df_focal['household'].nunique()

total_category_revenue = df[df['commodity'] == 'pasta']['dollar_sales'].sum()

# Calculate the Market Share of the focal brand (B)
market_share_B_focal = total_revenue_focal / total_category_revenue
print(f"Focal Brand Market Share (B): {market_share_B_focal:.2%}")

# Calculate the purchase frequency (W) of the focal brand
purchase_frequency_W_focal = total_baskets_focal / total_households_focal
print(f"Focal Brand Purchase Frequency (W): {purchase_frequency_W_focal:.2f}")
```

```
Focal Brand Market Share (B): 9.50%
Focal Brand Purchase Frequency (W): 2.06
```

4.3 3. Calculate data of competing brands

[23]:
```
last_complete_quarter = competitive_metrics['Quarter'].max()
last_quarter_data = competitive_metrics[(competitive_metrics['brand'] !=␣
↪'Mueller') &
                                        (competitive_metrics['Quarter'] ==␣
↪last_complete_quarter)]

# Calculate the market share (B) and purchase frequency (W) of each brand
```

```python
last_quarter_data['Market_Share_B'] = last_quarter_data['Total_Revenue'] /
 ↪last_quarter_data['Total_Revenue'].sum()
last_quarter_data['Purchase_Frequency_W'] = last_quarter_data['Total_Baskets'] /
 ↪ last_quarter_data['Total_Households']

# Sort by sales and extract the top 10 brands
top_10_brands_last_quarter = last_quarter_data.sort_values(by='Total_Revenue',
 ↪ascending=False).head(10)

# Select the relevant columns and print the B and W of the top 10 brands, reset
 ↪the index
top_10_brands_BW = top_10_brands_last_quarter[['brand', 'Market_Share_B',
 ↪'Purchase_Frequency_W']].reset_index(drop=True)
print(top_10_brands_BW)
```

```
                  brand  Market_Share_B  Purchase_Frequency_W
0         Private Label            0.20                  1.61
1                  Ragu            0.16                  1.47
2                 Prego            0.09                  1.41
3           Aunt Jemima            0.07                  1.22
4               Barilla            0.06                  1.32
5              Classico            0.06                  1.27
6 Private Label Premium            0.05                  1.27
7              Bertolli            0.03                  1.24
8               Ronzoni            0.03                  1.25
9             Creamette            0.03                  1.28

C:\Users\23968\AppData\Local\Temp\ipykernel_7344\1770371965.py:9:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  last_quarter_data['Market_Share_B'] = last_quarter_data['Total_Revenue'] /
last_quarter_data['Total_Revenue'].sum()
C:\Users\23968\AppData\Local\Temp\ipykernel_7344\1770371965.py:10:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  last_quarter_data['Purchase_Frequency_W'] = last_quarter_data['Total_Baskets']
/ last_quarter_data['Total_Households']
```

[ ]: