Quantium – Retail Strategy & Analytics (Task 1)

This notebook contains the solution for Task 1 of the Quantium Data Analytics Virtual Experience hosted on Forage. The goal is to analyze customer transaction data to derive meaningful insights into customer segments and chip sales.

In [2]:
```python
# Load required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import re
import datetime


# Load datasets
transactionData = pd.read_csv("Data/raw/QVI_transaction_data.csv")
customerData = pd.read_csv("Data/raw/QVI_purchase_behaviour.csv")
```

Data Overview

Let's take a look at the structure and contents of the datasets. We'll begin by inspecting the transactions dataset and checking column types, missing values, and sample rows.

In [6]:
```python
transactionData.info()
transactionData.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264836 entries, 0 to 264835
Data columns (total 8 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   DATE            264836 non-null  int64  
 1   STORE_NBR       264836 non-null  int64  
 2   LYLTY_CARD_NBR  264836 non-null  int64  
 3   TXN_ID          264836 non-null  int64  
 4   PROD_NBR        264836 non-null  int64  
 5   PROD_NAME       264836 non-null  object 
 6   PROD_QTY        264836 non-null  int64  
 7   TOT_SALES       264836 non-null  float64
dtypes: float64(1), int64(6), object(1)
memory usage: 16.2+ MB
```

Out[6]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES
0	43390	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0
1	43599	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3
2	43605	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9
3	43329	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	15.0
4	43330	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	13.8

In [7]:
```python
customerData.info()
customerData.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 72637 entries, 0 to 72636
Data columns (total 3 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   LYLTY_CARD_NBR    72637 non-null  int64 
 1   LIFESTAGE         72637 non-null  object
 2   PREMIUM_CUSTOMER  72637 non-null  object
dtypes: int64(1), object(2)
memory usage: 1.7+ MB
```

Out[7]:

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER
0	1000	YOUNG SINGLES/COUPLES	Premium
1	1002	YOUNG SINGLES/COUPLES	Mainstream
2	1003	YOUNG FAMILIES	Budget
3	1004	OLDER SINGLES/COUPLES	Mainstream
4	1005	MIDAGE SINGLES/COUPLES	Mainstream

Converting Integer to Date Format

The DATE column is stored as an integer. We will convert it to datetime format.

In [8]:
```
transactionData['DATE'] = pd.to_datetime(transactionData['DATE'], origin='1899-12-30', unit='D')
```

Filtering Non-Chip Products

We are only interested in potato chip products. Let’s remove entries like salsa.

In [11]:
```
transactionData = transactionData[~transactionData['PROD_NAME'].str.lower().str.contains('salsa')]
```

Extracting Pack Size

We'll extract the numeric value representing the pack size (in grams) from the product name.

In [13]:
```
transactionData['PACK_SIZE'] = transactionData['PROD_NAME'].str.extract(r'(\d+)').astype(float)
```

Extracting Brand Name

We'll use the first word in the product name as a proxy for the brand.

In [14]:
```
transactionData['BRAND'] = transactionData['PROD_NAME'].str.split().str[0]
transactionData['BRAND'].replace({'RED': 'RRD', 'SNBTS': 'SUNBITES'}, inplace=True)
```

```
C:\Users\prath\AppData\Local\Temp\ipykernel_24584\255876979.py:2: FutureWarning: A value is trying to be set on
a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on w
hich we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)'
or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  transactionData['BRAND'].replace({'RED': 'RRD', 'SNBTS': 'SUNBITES'}, inplace=True)
```

Outlier Detection

Let’s identify unusual values such as transactions with very high product quantities.

In [16]:
```
transactionData['PROD_QTY'].describe()
transactionData[transactionData['PROD_QTY'] > 100]
```

Out[16]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	BRAND
69762	2018-08-19	226	226000	226201	4	Dorito Corn Chp Supreme 380g	200	650.0	380.0	Dorito
69763	2019-05-20	226	226000	226210	4	Dorito Corn Chp Supreme 380g	200	650.0	380.0	Dorito

Removing Commercial Transactions

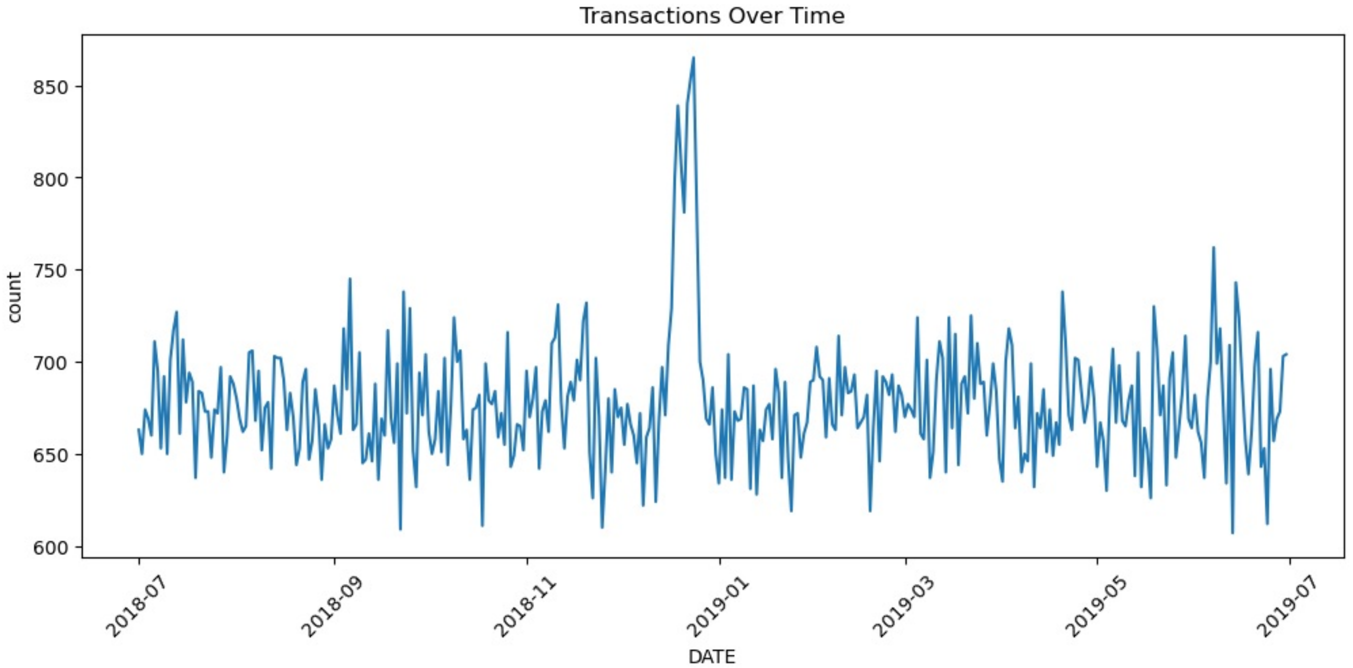
We will remove the customer who bought 200 chip packets in two separate transactions.

In [17]:
```
bad_customer = transactionData.loc[transactionData['PROD_QTY'] == 200, 'LYLTY_CARD_NBR'].values[0]
transactionData = transactionData[transactionData['LYLTY_CARD_NBR'] != bad_customer]
```

Transactions Over Time

Let’s plot the number of transactions by date to identify any missing or unusual patterns.

In [18]:
```
transactions_by_day = transactionData.groupby('DATE').size().reset_index(name='count')

plt.figure(figsize=(12,5))
sns.lineplot(data=transactions_by_day, x='DATE', y='count')
plt.title('Transactions Over Time')
plt.xticks(rotation=45)
plt.show()
```



Merging Customer Data

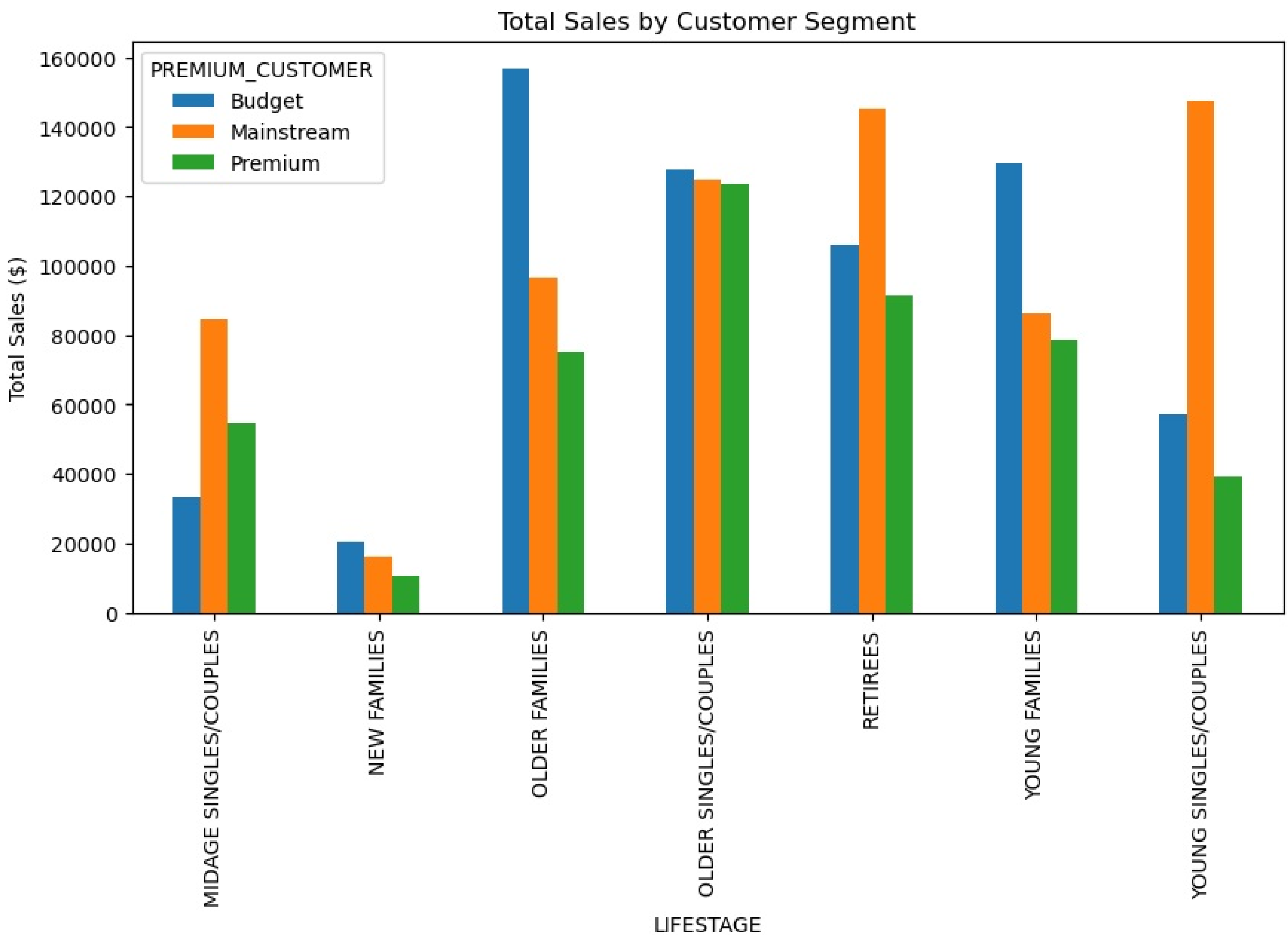
We will merge the transactions with the customer segments for further analysis.

In [19]:
```
data = transactionData.merge(customerData, how='left', on='LYLTY_CARD_NBR')
```

Customer Segment Insights

Let's analyze which segments (based on `LIFESTAGE` and `PREMIUM_CUSTOMER`) contribute most to chip sales.

In [26]:
```
# Total sales
data['SALES'] = data['TOT_SALES']
segment_sales = data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'])['SALES'].sum().unstack()

segment_sales.plot(kind='bar', figsize=(10,5), title='Total Sales by Customer Segment')
plt.ylabel('Total Sales ($)')
plt.show()
```



Statistical Test – Unit Price Difference Between Segments

An independent t-test was performed to determine whether the **unit price paid** by **Mainstream midage and young singles/couples** differs significantly from that paid by their **Budget and Premium counterparts**.

- **Null Hypothesis (H_0):** There is no significant difference in average unit prices between the two groups.
- **Alternative Hypothesis (H_1):** Mainstream customers pay a significantly different price per unit.

Test Results

- **T-statistic:** 37.6244
- **P-value:** < 0.0001

Conclusion

The t-test results in a **p-value < 0.0001**, which is **highly statistically significant**.
This means the **unit price for Mainstream midage and young singles/couples** is **significantly higher** than that of **Budget and Premium** customers in the same life stage categories.

This insight suggests that **Mainstream customers are likely less price-sensitive**, potentially due to preferences for **premium brands**, **convenience**, or **brand loyalty**.

In [28]:

```python
from scipy.stats import ttest_ind

# Filter relevant rows
subset = data[data['LIFESTAGE'].isin(['MIDAGE SINGLES/COUPLES', 'YOUNG SINGLES/COUPLES'])]

# Get unit price (TOT_SALES / PROD_QTY)
subset['UNIT_PRICE'] = subset['TOT_SALES'] / subset['PROD_QTY']

# Split by PREMIUM_CUSTOMER category
mainstream = subset[subset['PREMIUM_CUSTOMER'] == 'Mainstream']['UNIT_PRICE']
others = subset[subset['PREMIUM_CUSTOMER'].isin(['Budget', 'Premium'])]['UNIT_PRICE']

# Perform t-test
t_stat, p_value = ttest_ind(mainstream, others, equal_var=False)

print(f"T-statistic: {t_stat:.4f}")
print(f"P-value: {p_value:.6f}")
```

```
T-statistic: 37.6244
P-value: 0.000000
```

```
C:\Users\prath\AppData\Local\Temp\ipykernel_24584\3217738734.py:7: 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
  subset['UNIT_PRICE'] = subset['TOT_SALES'] / subset['PROD_QTY']
```

Preferred Pack Size – Mainstream Young Singles/Couples

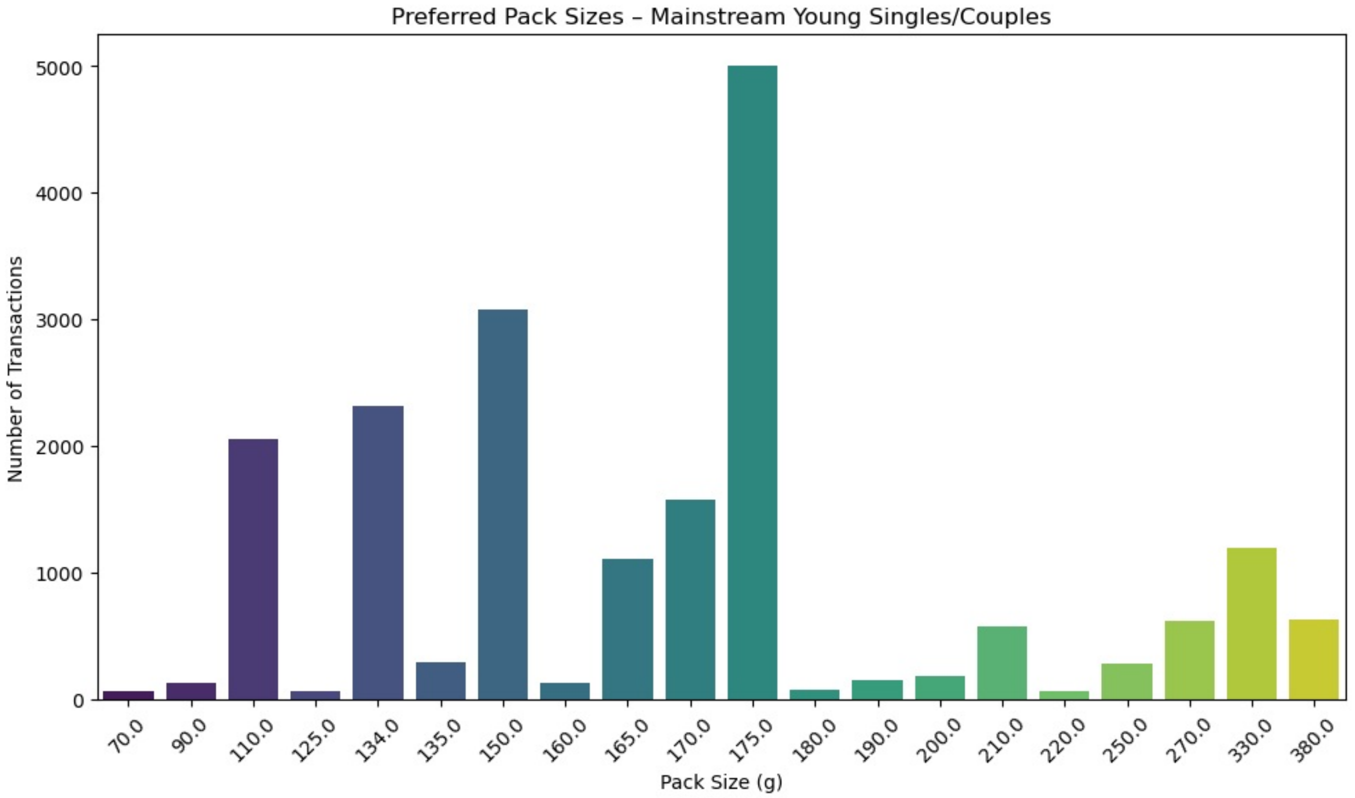
In this section, we focus on identifying the most preferred chip pack sizes among customers in the **Mainstream - Young Singles/Couples** segment.

This analysis helps us understand whether this segment tends to prefer smaller, single-serve packs or larger, shareable packs.

In [27]:

```python
# Filter the target segment
target_segment = data[
    (data['LIFESTAGE'] == 'YOUNG SINGLES/COUPLES') &
    (data['PREMIUM_CUSTOMER'] == 'Mainstream')
]

# Group by PACK_SIZE and count number of transactions
pack_size_pref = target_segment.groupby('PACK_SIZE').size().reset_index(name='count')

# Sort by count
pack_size_pref = pack_size_pref.sort_values('count', ascending=False)

# Plot
plt.figure(figsize=(10,6))
sns.barplot(data=pack_size_pref, x='PACK_SIZE', y='count', palette='viridis')
plt.title('Preferred Pack Sizes – Mainstream Young Singles/Couples')
plt.xlabel('Pack Size (g)')
plt.ylabel('Number of Transactions')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
C:\Users\prath\AppData\Local\Temp\ipykernel_24584\1930875315.py:15: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(data=pack_size_pref, x='PACK_SIZE', y='count', palette='viridis')
```



Preferred Pack Size – Mainstream Young Singles/Couples

The analysis of chip pack size preferences for the **Mainstream – Young Singles/Couples** segment reveals a clear buying behavior trend:

- The **175g pack size** stands out as the **most preferred**, with the highest transaction count (~5000).
- Other frequently purchased sizes include **150g**, **134g**, and **110g**, indicating a secondary preference range.
- **Larger pack sizes** such as **330g** and **380g** are **less favored**, suggesting limited appeal for bulk or sharing-oriented formats.

Interpretation:
These findings suggest that this customer segment leans toward **personal or convenience-based consumption**, likely driven by lifestyle factors such as on-the-go habits or solo snacking.

Recommendation:
To capitalize on this preference, retailers and marketers should:

- Focus promotions on **mid-sized packs (150–175g)**
- Bundle these sizes in multi-buy offers targeted at the **Mainstream – Young Singles/Couples** segment
- Consider packaging design and placement strategies that emphasize **portability and ease of use**