Task 1 Introduction

In this project, I've been approached by the Category Manager for Chips, who wants a better understanding the types of customers who purchase Chips and their purchasing behavior within the region.

The goal of this analysis is to answer key questions such as:

- Examine transaction data: Look for inconsistencies, missing data, outliers, correctly identified category items, and numeric data across all tables.
- Examine customer data: Check for similar issues in customer data, look for nulls and merge data after cleaning.
- Define the Metrics: Total Sales, drivers of sales, where the highest sales are coming from, etc.
- Create charts and note any trends or insights.
- Define recommendation from my insights, determine which segments we should be targeting. If packet sizes are relative and form conclusion about the analysis.

Importing required liraries and datasets

In [93]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker

pd.set_option('display.max_columns', None)
customer_df = pd.read_csv("Dataset/QVI_purchase_behaviour.csv")
transaction_df = pd.read_excel("Dataset/QVI_transaction_data.xlsx")
```

Examining the Transaction Dataset

In [4]:
```
print(transaction_df.info())
```

```
<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
None
```

I see that date is in integer format instead of date. Furthermore, I added a year and month column for additional filtering.

In [5]:
```
transaction_df_cleaned = transaction_df.copy()
transaction_df_cleaned['DATE'] = pd.to_datetime(transaction_df_cleaned['DATE'], ori
transaction_df_cleaned['YEAR'] = pd.to_datetime(transaction_df_cleaned['DATE']).dt.
transaction_df_cleaned['MONTH'] = pd.to_datetime(transaction_df_cleaned['DATE']).dt
transaction_df_cleaned
```

Out[5]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt175g	
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese 175g	
2	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	
3	2018-08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	
4	2018-08-18	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	
...	...	...	...	...	...	...	
264831	2019-03-09	272	272319	270088	89	Kettle Sweet Chilli And Sour Cream 175g	
264832	2018-08-13	272	272358	270154	74	Tostitos Splash Of Lime 175g	
264833	2018-11-06	272	272379	270187	51	Doritos Mexicana 170g	
264834	2018-12-27	272	272379	270188	42	Doritos Corn Chip Mexican Jalapeno 150g	
264835	2018-09-22	272	272380	270189	74	Tostitos Splash Of Lime 175g	

264836 rows × 10 columns

Extract the weight for every product for future dollar to weight analysis. Added a product price column to find the price of each item.

In [6]:

```
transaction_df_cleaned['PROD_PRICE_$'] = transaction_df_cleaned['TOT_SALES']/transa
transaction_df_cleaned['PROD_WEIGHT_G'] = transaction_df_cleaned['PROD_NAME'].str.e
transaction_df_cleaned['PROD_WEIGHT_G'] = transaction_df_cleaned['PROD_WEIGHT_G'].s
transaction_df_cleaned['PROD_WEIGHT_G'] = transaction_df_cleaned['PROD_WEIGHT_G'].a
transaction_df_cleaned.sample(10)
```

Out[6]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_C
91884	2019-01-03	160	160142	161009	48	Red Rock Deli Sp Salt & Truffle 150G	
181042	2018-12-30	191	191039	191994	87	Infuzions BBQ Rib Prawn Crackers 110g	
213245	2018-09-12	190	190117	190939	90	Tostitos Smoked Chipotle 175g	
251328	2019-02-05	172	172032	172941	45	Smiths Thinly Cut Roast Chicken 175g	
171357	2018-07-27	268	268371	264808	42	Doritos Corn Chip Mexican Jalapeno 150g	
25525	2018-09-17	25	25090	21787	14	Smiths Crnkle Chip Orgnl Big Bag 380g	
184206	2019-03-03	254	254192	254283	74	Tostitos Splash Of Lime 175g	
59361	2018-10-29	74	74029	72890	80	Natural ChipCo Sea Salt & Vinegr 175g	
220114	2018-11-18	71	71092	69511	92	WW Crinkle Cut Chicken 175g	
59338	2018-12-05	72	72358	72183	31	Infzns Crn Crnchers Tangy Gcamole 110g	

In [7]:

```
product_words = (
    transaction_df_cleaned['PROD_NAME']
    .dropna()
    .unique()
)
all_words = pd.Series(' '.join(product_words).split())
# Keep only alphabetic words which would exclude 200g, etc.
```

```
clean_words = all_words[all_words.str.isalpha()]
word_counts = clean_words.value_counts().reset_index()
word_counts.columns = ['word', 'count']
print(word_counts.head(20))
```

```
        word  count
0      Chips     21
1     Smiths     16
2    Crinkle     14
3        Cut     14
4     Kettle     13
5       Salt     12
6     Cheese     12
7   Original     10
8    Doritos      9
9       Chip      9
10     Salsa      9
11      Corn      8
12  Pringles      8
13       RRD      8
14   Chicken      7
15        WW      7
16       Sea      6
17      Sour      6
18    Thinly      5
19    Crisps      5
```

We only want chip items, and will remove all non chip items. In this case, salsa is the only non chip item

In [8]:
```
is_salsa = transaction_df_cleaned['PROD_NAME'].str.lower().str.contains('salsa') #
transaction_df_cleaned = transaction_df_cleaned[~is_salsa] # filter out all instanc
```

Use transaction_df_cleaned.describe() to find key mathematical metrics and find potential outliers. The max production quantity seems signifcantly larger, (mean = 1.90) and will be investigated further.

In [9]:
```
transaction_df_cleaned.describe()
```

Out[9]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR
count	246742	246742.000000	2.467420e+05	2.467420e+05	246742.000000
mean	2018-12-30 01:19:01.211467520	135.051098	1.355310e+05	1.351311e+05	56.351789
min	2018-07-01 00:00:00	1.000000	1.000000e+03	1.000000e+00	1.000000
25%	2018-09-30 00:00:00	70.000000	7.001500e+04	6.756925e+04	26.000000
50%	2018-12-30 00:00:00	130.000000	1.303670e+05	1.351830e+05	53.000000
75%	2019-03-31 00:00:00	203.000000	2.030840e+05	2.026538e+05	87.000000
max	2019-06-30 00:00:00	272.000000	2.373711e+06	2.415841e+06	114.000000
std	NaN	76.787096	8.071528e+04	7.814772e+04	33.695428

In [10]:

```
transaction_df_cleaned.sort_values(by="PROD_QTY", ascending=False).head(10)
```

Out[10]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PR
69763	2019-05-20	226	226000	226210	4	Dorito Corn Chp Supreme 380g	
69762	2018-08-19	226	226000	226201	4	Dorito Corn Chp Supreme 380g	
135225	2019-05-15	46	46296	42138	81	Pringles Original Crisps 134g	
69523	2019-05-15	71	71142	69852	96	WW Original Stacked Chips 160g	
69502	2018-08-18	55	55144	49328	44	Thins Chips Light& Tangy 175g	
69496	2018-08-15	49	49303	45789	14	Smiths Crnkle Chip Orgnl Big Bag 380g	
69486	2019-05-16	45	45006	40460	37	Smiths Thinly Swt Chli&S/Cream175G	
69483	2018-08-15	43	43126	39445	25	Pringles SourCream Onion 134g	
69474	2018-08-18	33	33138	30332	68	Pringles Chicken Salt Crips 134g	
69472	2018-08-17	32	32193	29196	110	WW Original Corn Chips 200g	

In [11]:
```
transaction_df_cleaned[transaction_df_cleaned["LYLTY_CARD_NBR"] == 226000]
```

Out[11]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QT
69762	2018-08-19	226	226000	226201	4	Dorito Corn Chp Supreme 380g	2(
69763	2019-05-20	226	226000	226210	4	Dorito Corn Chp Supreme 380g	2(

It seems that the customer that made these two large purchases are the same pearson, likely a yearly inventory stock up transactions. This customer will be eliminated to avoid any outlier due to it being an abnormal purchase.

In [12]:
```
transaction_df_cleaned = transaction_df_cleaned[transaction_df_cleaned["LYLTY_CARD_
transaction_df_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 246740 entries, 0 to 264835
Data columns (total 12 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   DATE            246740 non-null  datetime64[ns]
 1   STORE_NBR       246740 non-null  int64
 2   LYLTY_CARD_NBR  246740 non-null  int64
 3   TXN_ID          246740 non-null  int64
 4   PROD_NBR        246740 non-null  int64
 5   PROD_NAME       246740 non-null  object
 6   PROD_QTY        246740 non-null  int64
 7   TOT_SALES       246740 non-null  float64
 8   YEAR            246740 non-null  int32
 9   MONTH           246740 non-null  int32
 10  PROD_PRICE_$    246740 non-null  float64
 11  PROD_WEIGHT_G   246740 non-null  int32
dtypes: datetime64[ns](1), float64(2), int32(3), int64(5), object(1)
memory usage: 21.6+ MB
```

In [13]:
```
print(transaction_df_cleaned.isnull().sum())
```

```
DATE              0
STORE_NBR         0
LYLTY_CARD_NBR    0
TXN_ID            0
PROD_NBR          0
PROD_NAME         0
PROD_QTY          0
TOT_SALES         0
YEAR              0
MONTH             0
PROD_PRICE_$      0
PROD_WEIGHT_G     0
dtype: int64
```

In [14]:
```
len(transaction_df_cleaned["DATE"].unique())
```

Out[14]: 364

There seems to be one day where no transactions are made. That day should still be filled.

In [15]:
```
all_dates = pd.date_range( # Get all the dates within this period
    start=transaction_df_cleaned['DATE'].min(),
    end=transaction_df_cleaned['DATE'].max(),
    freq='D'
)
daily_sales = transaction_df_cleaned.groupby('DATE')['TOT_SALES'].sum().reset_index
daily_sales.set_index('DATE', inplace=True)
# Reindex to include all dates in the range
daily_sales = daily_sales.reindex(all_dates)
daily_sales.index.name = 'DATE'
# Fill missing sales with 0
daily_sales['TOT_SALES'] = daily_sales['TOT_SALES'].fillna(0)
daily_sales
```

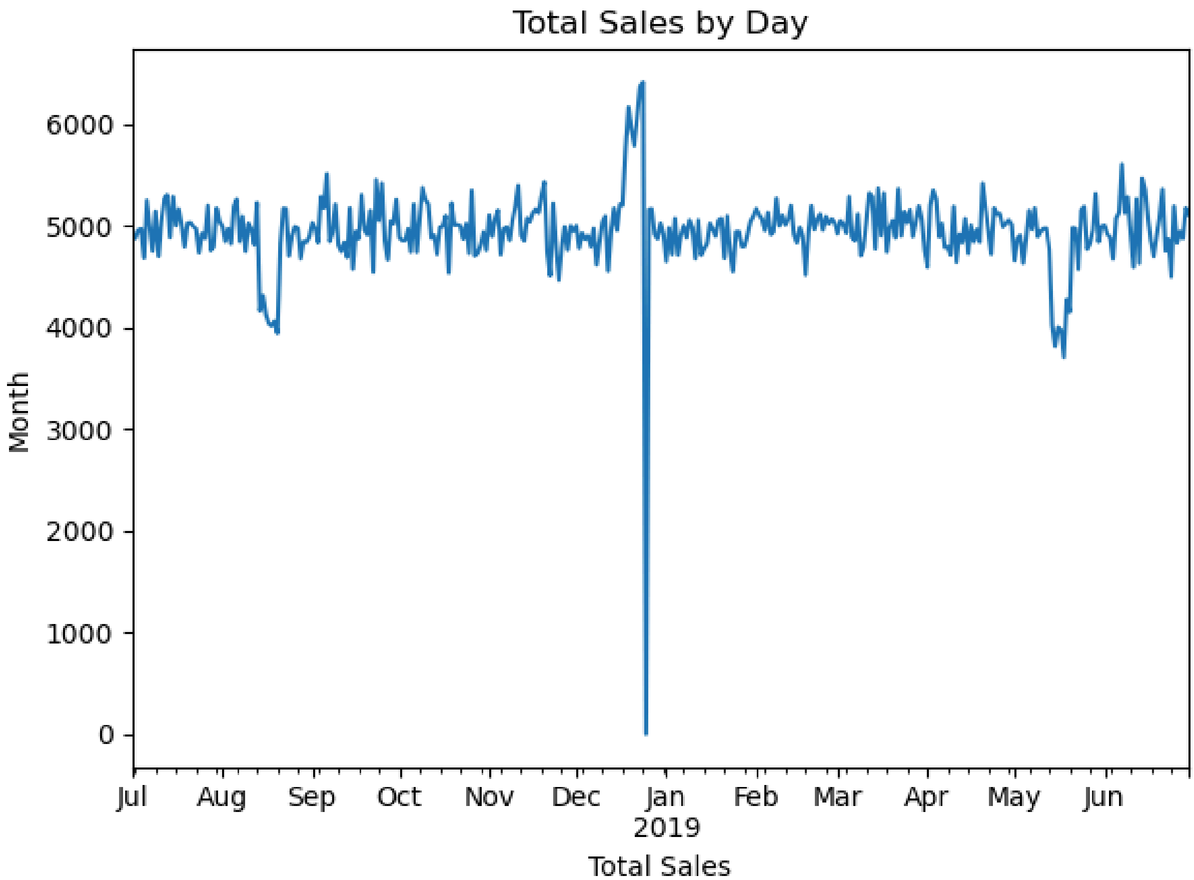
Out[15]:

DATE	TOT_SALES
2018-07-01	4920.1
2018-07-02	4877.0
2018-07-03	4954.7
2018-07-04	4968.1
2018-07-05	4682.0
...	...
2019-06-26	4829.7
2019-06-27	4941.3
2019-06-28	4876.6
2019-06-29	5177.6
2019-06-30	5108.4

365 rows × 1 columns

In [16]:

```
daily_sales.plot(kind='line')
plt.title("Total Sales by Day")
plt.xlabel("Total Sales")
plt.ylabel("Month")
plt.legend().set_visible(False)
plt.tight_layout()
plt.show()
```



There seems to be a day in late december that had no sales, it was likely due to a holiday where the store was closed.

Examining the Customer Dataset

In [17]:
```
customer_df.info()
```

```
<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
```

In [38]:
```
print(f'LYLTY_CARD_NBR: {len(customer_df["LYLTY_CARD_NBR"].unique())}')
print(f'LIFESTAGE: {len(customer_df["LIFESTAGE"].unique())}')
print(f'PREMIUM_CUSTOMER: {len(customer_df["PREMIUM_CUSTOMER"].unique())}')
```

```
LYLTY_CARD_NBR: 72637
LIFESTAGE: 7
PREMIUM_CUSTOMER: 3
```

In [27]:
```
customer_df.isnull().sum()
```

Out[27]:
```
LYLTY_CARD_NBR      0
LIFESTAGE           0
PREMIUM_CUSTOMER    0
dtype: int64
```

In [41]:
```
store_merged_df = customer_df.merge(transaction_df_cleaned)
store_merged_df
```

Out[41]:

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER	DATE	STORE_NBR	T)
0	1000	YOUNG SINGLES/COUPLES	Premium	2018-10-17	1	
1	1002	YOUNG SINGLES/COUPLES	Mainstream	2018-09-16	1	
2	1003	YOUNG FAMILIES	Budget	2019-03-07	1	
3	1003	YOUNG FAMILIES	Budget	2019-03-08	1	
4	1004	OLDER SINGLES/COUPLES	Mainstream	2018-11-02	1	
...	...	...	...	...	...	
246735	2370651	MIDAGE SINGLES/COUPLES	Mainstream	2018-08-03	88	2
246736	2370701	YOUNG FAMILIES	Mainstream	2018-12-08	88	2
246737	2370751	YOUNG FAMILIES	Premium	2018-10-01	88	2
246738	2370961	OLDER FAMILIES	Budget	2018-10-24	88	2
246739	2373711	YOUNG SINGLES/COUPLES	Mainstream	2018-12-14	88	2

246740 rows × 14 columns

Defining Metrics

Store Overview Metrics:

- Total Sales: Sum of TOT_SALES, used to show revenue
- Total Transactions: Count of TXN_ID, used to show activity volume
- Sales by Year-Month, used to determine sales over time

Customer demographic Metrics Grouped by Stores:

- Average Sales Per Customer: TOT_SALES / Unique Customers, used to show individual revenue
- Transaction by Lifestage, and Premium Customer: Used to determine shopper identity and who the most valuable customers are

Item Classification Metrics:

- Average Item Per Transactions: COUNT PROD_NAME / TXN_ID, used to show individual volume
- Sales by Weight: Determine which size items are most purchased and sold

Store Overview Analysis:

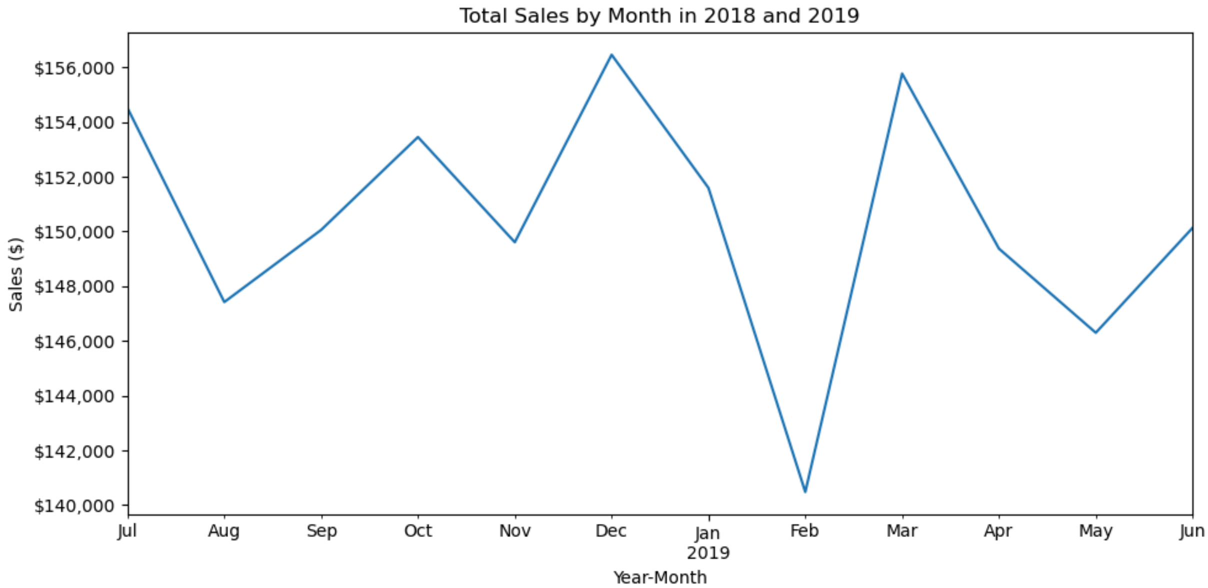
- Total Sales: Sum of TOT_SALES, used to show revenue
- Total Transactions: Count of TXN_ID, used to show activity volume
- Sales by Year-Month, used to determine sales over time

In [64]:
```
tot_revenue = "{:,}".format(round(store_merged_df["TOT_SALES"].sum()))
tot_transactions = "{:,}".format(len(store_merged_df["TXN_ID"].unique()))
print(f"The total revenue between all stores between July 2018 - June 2019 is ${tot
print(f"The total transactions between all stores between July 2018 - June 2019 is
```

```
The total revenue between all stores between July 2018 - June 2019 is $1,805,178
The total transactions between all stores between July 2018 - June 2019 is 245,255
```

In [68]:
```
monthly_sales = store_merged_df.groupby(
    store_merged_df['DATE'].dt.to_period('M') # group by month
)['TOT_SALES'].sum()
monthly_sales.plot(kind='line', figsize=(10, 5))
plt.title('Total Sales by Month in 2018 and 2019')
plt.ylabel('Sales ($)')
plt.xlabel('Year-Month')
plt.gca().yaxis.set_major_formatter(ticker.StrMethodFormatter('${x:,.0f}'))
plt.tight_layout()
plt.plot()
```

Out[68]: `[]`



Monthly Sales Analysis

- Monthly sales from July 2018 to June 2019 fluctuated between $140,000and$156,000, an approximate 10% variation. This reflects a stable financial performance throughout the year. Sales peaked in December, likely due to seasonal demand, which presents an opportunity for holiday promotions.
- The lowest sales occurred in February, potentially due to reduced demand following high volume holiday purchases. This is confirmed as March had the second highest monthly sale, likely to mass restock after finishing remaining supplies in February.
- The graph reveals an alternating monthly sales pattern, where peaks are followed by dips, likely due to typical consumer restocking behavior. This pattern is common in grocery retail, where high-purchase months are followed by lower ones as customers use up their inventory. To avoid overstocking and reduce volatility, bundling or targeted promotions during slower months could help drive steady revenue.
- Overall, the consistent monthly range indicates steady and predictable market demand, offering a strong foundation for category planning and future promotional strategies.

Customer demographic Metrics Grouped by Stores:

- Average Sales Per Customer: TOT_SALES / Unique Customers, used to show individual revenue
- Transaction by Lifestage, and Premium Customer: Used to determine shopper identity and who the most valuable customers are

In [138…

```
avg_sales_per_customer = store_merged_df.groupby("STORE_NBR").agg({
    "TOT_SALES": "sum",
    "LYLTY_CARD_NBR": "nunique"
})
avg_sales_per_customer["AVG_SALES_PER_CUSTOMER"] = (
    avg_sales_per_customer["TOT_SALES"] / avg_sales_per_customer["LYLTY_CARD_NBR"]
)
```

```
avg_sales_per_customer["PREMIUM_CUSTOMER"] = store_merged_df["PREMIUM_CUSTOMER"]
avg_sales_per_customer
```

Out[138…

	TOT_SALES	LYLTY_CARD_NBR	AVG_SALES_PER_CUSTOMER	PREMIUM_CUSTOM
STORE_NBR				
1	2223.90	332	6.698494	Mainstre
2	1854.00	298	6.221477	Bud
3	12149.65	362	33.562569	Bud
4	13709.25	378	36.267857	Mainstre
5	8802.20	237	37.140084	Mainstre
...	...	...	...	
268	2421.85	321	7.544704	Bud
269	10470.70	251	41.715936	Premi
270	10519.05	243	43.288272	Mainstre
271	8952.30	239	37.457322	Mainstre
272	4398.95	282	15.599113	Mainstre

271 rows × 4 columns

In [139…

```
plt.figure(figsize=(10,6))
sns.scatterplot(
    data=avg_sales_per_customer,
    x="LYLTY_CARD_NBR",
    y="AVG_SALES_PER_CUSTOMER",
    hue="PREMIUM_CUSTOMER",
    palette="tab10",
)
plt.title("Customer Count vs Avg Sales Per Customer")
plt.xlabel("Number of Unique Customers")
plt.ylabel("Avg Sales Per Customer ($)")
plt.grid(True)
plt.legend(title="Premium Customer")
plt.tight_layout()
plt.show()
```

Customer Count vs Average Sales Analysis

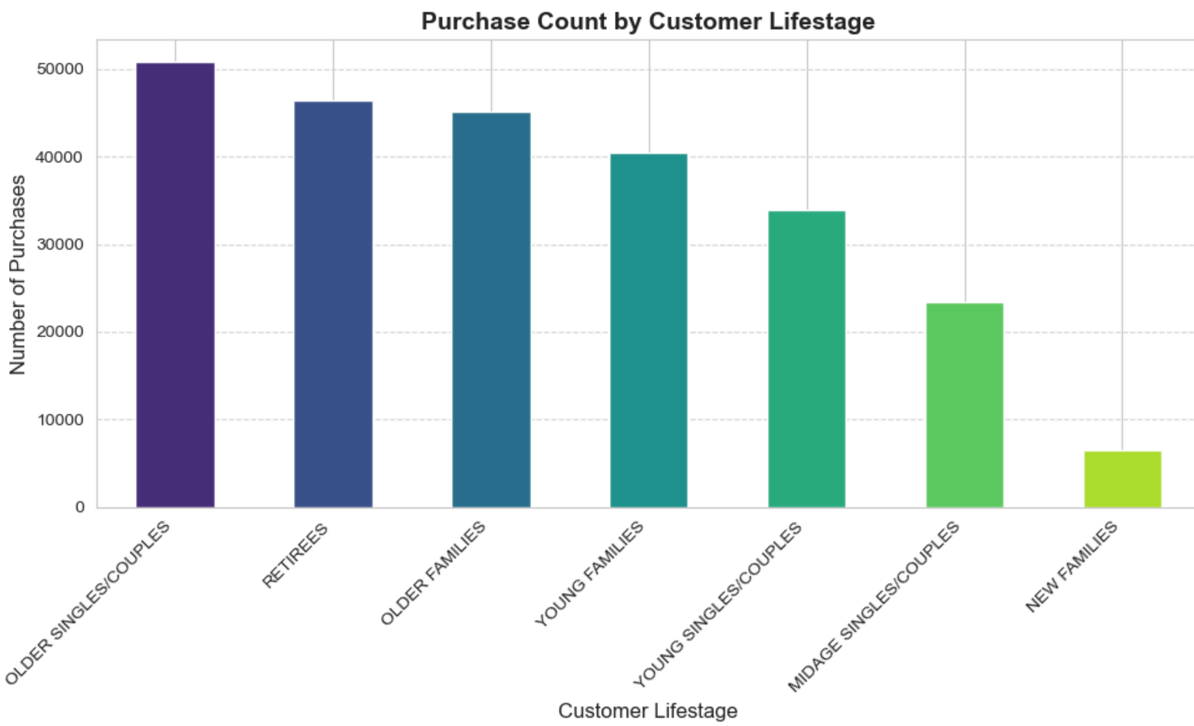
- A small portion of stores (~10) have a single-digit number of unique customers, suggesting these locations are likely closed or non-operational and should be excluded from further analysis.
- Another small portions of stores have around 40 - 70 unique customers with fairly low average sales per customers, these stores may be located in more rural regions. One potential option could be offering value based promotion, such as discounting items near expiration date to encourage more frequent purchases.
- The majority of stores seem to between 220 - 400 unique customers with varying average sales. The store seems to be seperated into 3 main categories by Average Sales Per Customer

1. $45 - 30$: These stores serve many premium and mainstream customers, who are likely to purchase larger or more expensive items. Surprisingly, budget shoppers are still present in this group, to a lesser extent. Most stores have either ~250 or ~350-400 unique customers, suggesting either a wealthier customer base or larger stores.
2. $30 - 15$: This store still lean towards premium and mainstream customers, surprisingly having a smaller portion of customer base as budget customers. This is likely due to budget customers preferring the cheaper alternatives, even if it means to sacrafice quality. Least stores are within this region, indicating customers often preferring the two extremes.
3. Less than $15: These stores have a fairly even distribution of customer base, though prefering budget customers. These stores attract between 250-350 unique customers, indicating a consistent customer base despite lower average revenue.

In [148…

```
sns.set_style("whitegrid")

customer_lifestage = store_merged_df.groupby("LIFESTAGE")["LYLTY_CARD_NBR"].count()
plt.figure(figsize=(10,6))
bars = customer_lifestage.plot(kind="bar", color=sns.color_palette("viridis", len(c
plt.title('Purchase Count by Customer Lifestage', fontsize=14, weight='bold')
plt.xlabel('Customer Lifestage', fontsize=12)
plt.ylabel('Number of Purchases', fontsize=12)
plt.legend().remove()
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



In [150…

```
customer_quartile_df = store_merged_df.copy()
customer_quartile_df["PRICE_QUARTILE"] = pd.qcut(customer_quartile_df["PROD_PRICE_$
customer_quartile_df["WEIGHT_QUARTILE"] = pd.qcut(customer_quartile_df["PROD_WEIGHT
customer_quartile_df
```

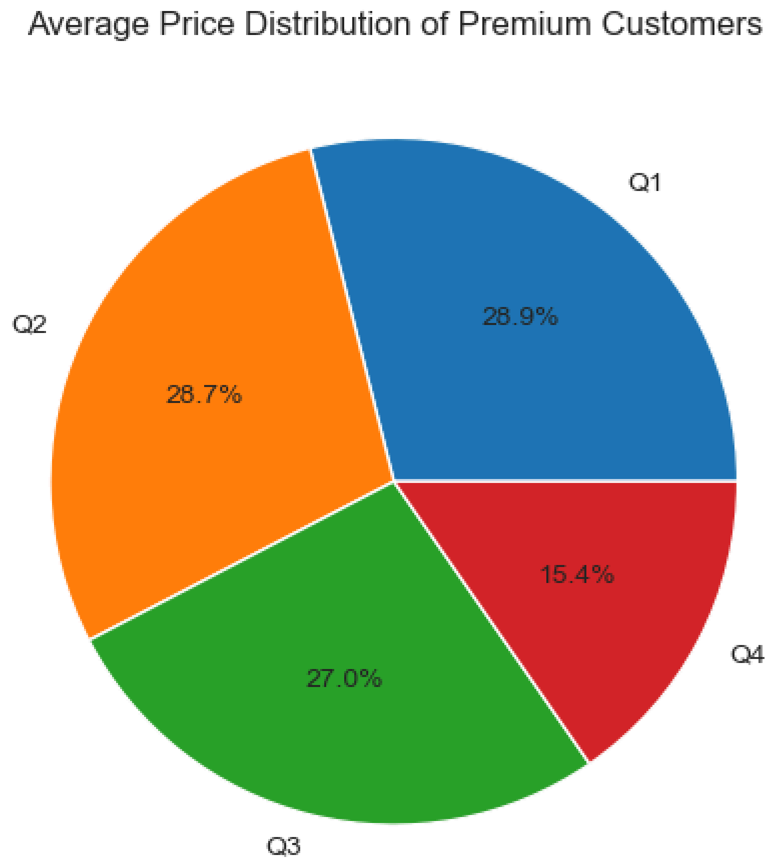
Out[150…

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER	DATE	STORE_NBR	T)
0	1000	YOUNG SINGLES/COUPLES	Premium	2018-10-17	1	
1	1002	YOUNG SINGLES/COUPLES	Mainstream	2018-09-16	1	
2	1003	YOUNG FAMILIES	Budget	2019-03-07	1	
3	1003	YOUNG FAMILIES	Budget	2019-03-08	1	
4	1004	OLDER SINGLES/COUPLES	Mainstream	2018-11-02	1	
...	...	...	...	...	...	
246735	2370651	MIDAGE SINGLES/COUPLES	Mainstream	2018-08-03	88	2
246736	2370701	YOUNG FAMILIES	Mainstream	2018-12-08	88	2
246737	2370751	YOUNG FAMILIES	Premium	2018-10-01	88	2
246738	2370961	OLDER FAMILIES	Budget	2018-10-24	88	2
246739	2373711	YOUNG SINGLES/COUPLES	Mainstream	2018-12-14	88	2

246740 rows × 16 columns

In [156…

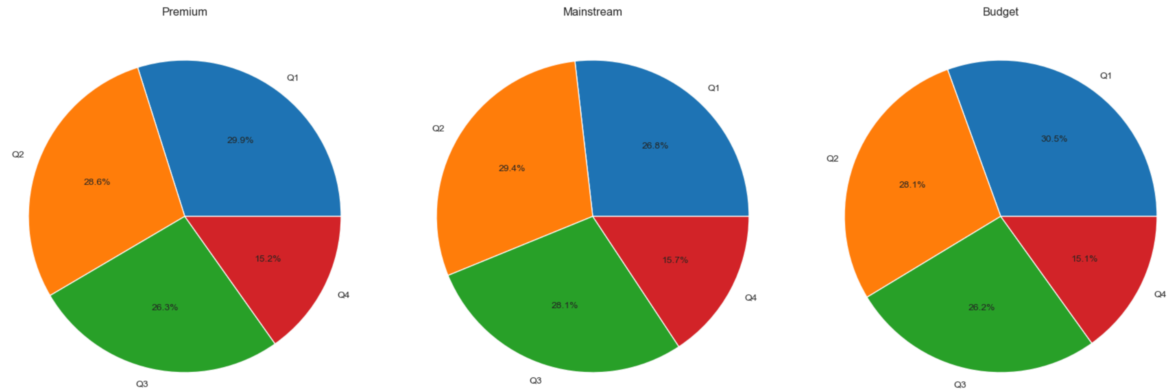
```
customer_quartile_df_average_price = customer_quartile_df["PRICE_QUARTILE"].value_c
customer_quartile_df_average_price.plot(
    kind="pie",
    autopct='%1.1f%%',
    ylabel=''
)
plt.title("Average Price Distribution of Premium Customers")
plt.tight_layout()
plt.show()
```



In [157…

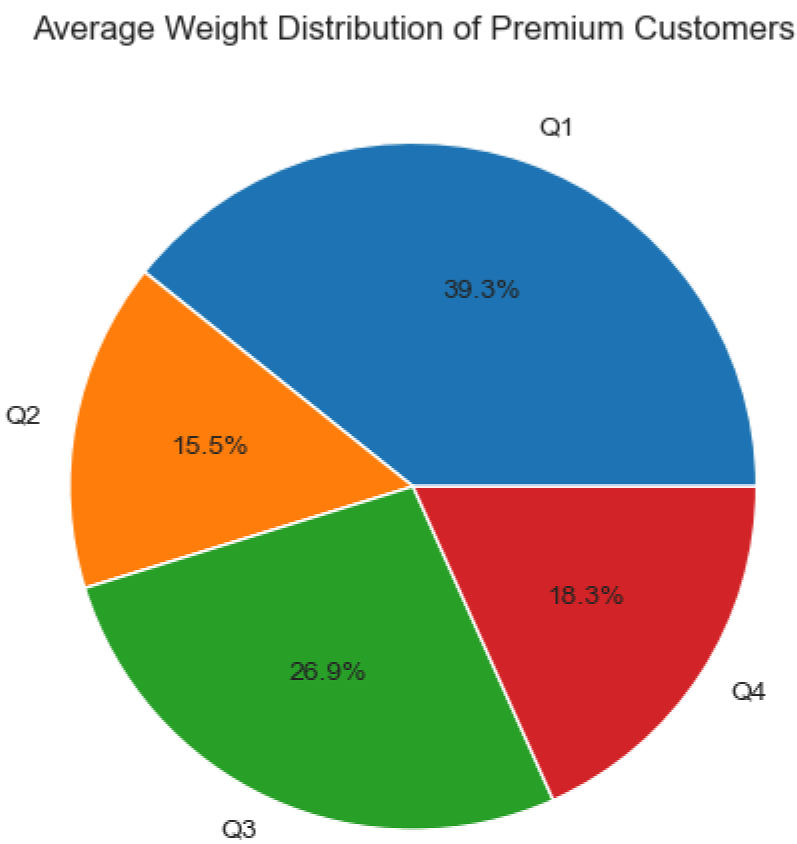
```
customer_quartile_df_customers = customer_quartile_df.groupby("PREMIUM_CUSTOMER")
customer_quartile_df_customers = customer_quartile_df_customers["PRICE_QUARTILE"].v
customer_quartile_df_customers_unstack = customer_quartile_df_customers.unstack()

fig, axes = plt.subplots(1, 3, figsize=(18, 6))
segments = customer_quartile_df["PREMIUM_CUSTOMER"].unique()
for i, segment in enumerate(segments):
    data = customer_quartile_df[customer_quartile_df["PREMIUM_CUSTOMER"] == segment
    data.plot(
        kind='pie',
        autopct='%1.1f%%',
        ylabel='',
        ax=axes[i],
        title=segment
    )
plt.tight_layout()
plt.show()
```



In [154…

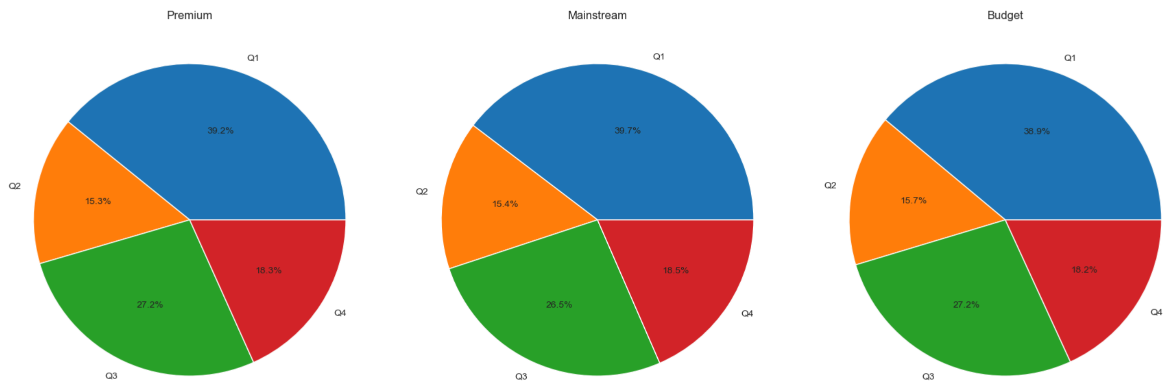
```
customer_quartile_df_average_weight = customer_quartile_df["WEIGHT_QUARTILE"].value
customer_quartile_df_average_weight.plot(
    kind="pie",
    autopct='%1.1f%%',
    ylabel=''
)
plt.title("Average Weight Distribution of Premium Customers")
plt.tight_layout()
plt.show()
```



In [155…

```
customer_quartile_df_customers = customer_quartile_df.groupby("PREMIUM_CUSTOMER")
customer_quartile_df_customers = customer_quartile_df_customers["WEIGHT_QUARTILE"].
customer_quartile_df_customers_unstack = customer_quartile_df_customers.unstack()
```

```python
fig, axes = plt.subplots(1, 3, figsize=(18, 6))
segments = customer_quartile_df["PREMIUM_CUSTOMER"].unique()
for i, segment in enumerate(segments):
    data = customer_quartile_df[customer_quartile_df["PREMIUM_CUSTOMER"] == segment
    data.plot(
        kind='pie',
        autopct='%1.1f%%',
        ylabel='',
        ax=axes[i],
        title=segment
    )
plt.tight_layout()
plt.show()
```



Price vs Weight Distrbution Analysis

Price Distribution

- The price distribution is evenly distributed among customer's premium status. All customers show similar purchasing behavior when segmented by price quartiles.
- Even premium customers, typically assumed to prioritize quality over cost, demonstrate similarly toward value.
- These findings imply that price sensitivity is a general trend among all customer types, not just budget conscious ones. Future promotions could focus on highlighting value, even for higher tier items.

Weight Distribution

- The weight distribution is evenly distributed among customer's premium status. All customers have similar purchasing behavior when segmented by weight quartiles.
- The largest distribution of items sold are the lightest items. From previous observations, these items are smaller snacks which are cheaper and easily consumable.
- Products that are slightly below average (Q2) are the least purchased. This may be caused by higher price, too small to share with a group, or too much for a single person to purchase. This trend suggests that the store manager should either purchase items that are smaller in size or larger.