DATA LOADING

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remoun
```

```
file_path = '/content/drive/My Drive/QVI_purchase_behaviour.csv'
purchase_df = pd.read_csv(file_path)
```

```
file_path2 = '/content/drive/My Drive/QVI_transaction_data.xlsx'
transaction_df = pd.read_excel(file_path2)
```

```
purchase_df.head(3)
```

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER
0	1000	YOUNG SINGLES/COUPLES	Premium
1	1002	YOUNG SINGLES/COUPLES	Mainstream
2	1003	YOUNG FAMILIES	Budget

Next steps: Generate code with purchase_df View recommended plots New interactive sheet

```
transaction_df.head(3)
```

	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

DATA PREPROCESSING

- Check for Null Values
  - No null values were found in both DataFrames.
- Check for Duplicate Values
  - Found one duplicate row in the transaction DataFrame.
- Correcting Data Types
  - The Date column has been set to the date format.
- Creating New Columns
  - Created two new columns: Packet_Size and Brands for the transaction DataFrame.
- Removing Unwanted Rows
  - Removed rows that are not related to chips or do not belong to the chips brand (specifically, rows with 'Salsa').
- Correcting Misspelled Brand Names
  - Corrected brand names that were misspelled.
- Removing Outliers
  - Removed outliers found in the TOTAL_SALES and PDT_QTY columns.

Checking for missing values in both the dataframes

```
print(purchase_df.isnull().sum())
```

```
LYLTY_CARD_NBR      0
LIFESTAGE           0
```

```
PREMIUM_CUSTOMER    0
dtype: int64
```

```
purchase_df.duplicated().sum()
```

```
0
```

```
print(transaction_df.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
dtype: int64
```

```
transaction_df.duplicated().sum()
```

```
1
```

```
transaction_df[transaction_df.duplicated(keep = False)]
```

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES
124843	43374	107	107024	108462	45	Smiths Thinly Cut Roast Chicken 175g	2	6.0
124845	43374	107	107024	108462	45	Smiths Thinly Cut Roast Chicken 175g	2	6.0

```
# Remove duplicates while keeping the first occurrence (drop the last)
transaction_df.drop_duplicates(keep='last', inplace=True)
```

```
transaction_df.duplicated().sum()
```

```
0
```

Checking for data types

```
purchase_df.dtypes
```

	0
LYLTY_CARD_NBR	int64
LIFESTAGE	object
PREMIUM_CUSTOMER	object

dtype: object

```
transaction_df.dtypes
#date datatype has to be changed to better understand the data
```

	0
DATE	int64
STORE_NBR	int64
LYLTY_CARD_NBR	int64
TXN_ID	int64
PROD_NBR	int64
PROD_NAME	object
PROD_QTY	int64
TOT_SALES	float64

dtype: object

```
transaction_df['DATE'] = pd.to_datetime(transaction_df['DATE'], unit ='D',origin = '1899-12-30')
#this line of code effectively transforms a column of integer values representing days since a specific date into a more use
#enabling easier manipulation and analysis of date-related data within the DataFrame.
```

```
unique_date = transaction_df['DATE'].unique()
len(unique_date)
```

```
364
```

```
#find out which date is missing data
# Create sequence of date
all_dates = list(pd.to_datetime(range(365), unit='D', origin='2018-07-01'))
missing_date = [dt for dt in all_dates if dt not in transaction_df['DATE'].unique()][0]

missing_date

#christmas day data is missing as its a public holiday
```

```
Timestamp('2018-12-25 00:00:00')
```

Explanation of Parameters: unit='D': Indicates that the integer values in the DATE column represent the number of days. origin='1899-12-30': Sets the starting point (epoch) for the date calculation. This is commonly used for converting Excel serial dates, which count days from December 30, 1899

```
#lets check the data types again
transaction_df.dtypes
```

	0
DATE	datetime64[ns]
STORE_NBR	int64
LYLTY_CARD_NBR	int64
TXN_ID	int64
PROD_NBR	int64
PROD_NAME	object
PROD_QTY	int64
TOT_SALES	float64

dtype: object

```
#lets create a new column Packet_size and convert it into numeric format
transaction_df['PACKET_SIZE'] = transaction_df['PROD_NAME'].str.extract(r'(\d+)', expand=False)
transaction_df['PACKET_SIZE'] = pd.to_numeric(transaction_df['PACKET_SIZE'], errors='coerce')

# Print the DataFrame to see the extracted numbers or the packet size
transaction_df.head()
```

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACKET_SIZE
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0	175
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3	175
2	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9	170
[illegible]	2018-08-	[illegible]	[illegible]	[illegible]	[illegible]	Smiths Chip Thinly	[illegible]	[illegible]	[illegible]

```
#check the packet_size datatype
transaction_df.dtypes
```

```
                              0
         DATE      datetime64[ns]
    STORE_NBR               int64
LYLTY_CARD_NBR              int64
       TXN_ID               int64
     PROD_NBR               int64
    PROD_NAME              object
     PROD_QTY               int64
    TOT_SALES             float64
  PACKET_SIZE               int64

dtype: object
```

```
#len(UniquePdtsName)
```

```
# This operation removes any rows where the PROD_NAME column contains the substring "Salsa," ignoring case differences
transaction_df = transaction_df[~transaction_df['PROD_NAME'].str.contains('Salsa', case=False, na=False)]
```

```
transaction_df['BRAND'] = transaction_df['PROD_NAME'].str.split(' ').str[0]
#The code creates a new column Brand in the DataFrame transaction_df by extracting the first word from each product name in
```

```
transaction_df['BRAND'].value_counts()
```

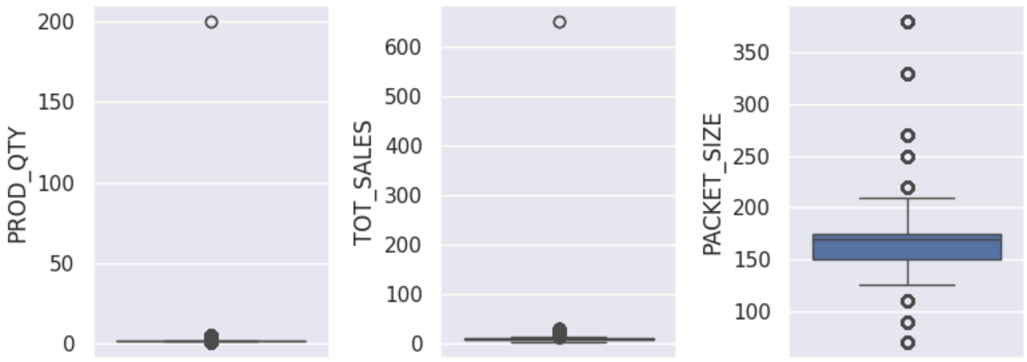
	count
BRAND	
Kettle	41288
Smiths	27389
Pringles	25102
Doritos	22041
Thins	14075
RRD	11894
Infuzions	11057
WW	10320
Cobs	9693
Tostitos	9471
Twisties	9454
Tyrrells	6442
Grain	6272
Natural	6050
Cheezels	4603
CCs	4551
Red	4427
Dorito	3185
Infzns	3144
Smith	2963
Cheetos	2927
Snbts	1576
Burger	1564
Woolworths	1516
GrnWves	1468
Sunbites	1432
NCC	1419
French	1418

dtype: int64

```
#the code corrects the brand names
transaction_df['BRAND'] = transaction_df['BRAND'].replace({
    r'\bSmith\b': 'Smiths',
    r'\bDorito\b': 'Doritos',
    r'\bGrnWves|Grain\b': 'Grain Waves',
    r'\bNatural|NCC\b': 'Natural Chip Co',
    r'\bInfzns\b': 'Infuzions',
    r'\bRed\b': 'RRD',
    r'\bSnbts\b': 'Sunbites',
    r'\bWW\b': 'Woolworths',
    r'\Burger\b': 'Burger Rings'

}, regex=True)
```

Removing Outliers from customer transaction data

```
# analysing the outliers in total sales , product quantity and packet_size columns
sns.set_theme()
fig, ax = plt.subplots(ncols=3, figsize=(8,3))

sns.boxplot(
    data = transaction_df,
    y = 'PROD_QTY',
    ax=ax[0]
)
sns.boxplot(
    data = transaction_df,
    y = 'TOT_SALES',
    ax=ax[1]
)

sns.boxplot(
    data = transaction_df,
    y = 'PACKET_SIZE',
    ax=ax[2]

)
fig.tight_layout()
```



```
# Product Quantity value 200 is an outlier .
transaction_df[transaction_df['PROD_QTY'] == 200]
```

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

```
transaction_df[transaction_df['TOT_SALES']>= 600]
```

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

```
# lets remove the outlier customer with id = 226000
transaction_df = transaction_df[~(transaction_df['LYLTY_CARD_NBR'] == 226000)]


#lets create 2 more columns 'MONTH' name  and 'DAY' name for the transaction DataFrame

transaction_df['MONTH'] = transaction_df['DATE'].dt.month_name()
transaction_df['DAY'] = transaction_df['DATE'].dt.day_name()
```

```
<ipython-input-101-14f826e88e73>:3: 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-
  transaction_df['MONTH'] = transaction_df['DATE'].dt.month_name()
<ipython-input-101-14f826e88e73>:4: 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-
  transaction_df['DAY'] = transaction_df['DATE'].dt.day_name()
```

```
transaction_df.head()
```

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACKET_SIZE	BRAND	MONTH	
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0	175	Natural Chip Co	October	Wednes
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3	175	CCs	May	Tues
2	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9	170	Smiths	May	Mor
3	2018-08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	15.0	175	Smiths	August	Fr

EXPLORATORY DATA ANALYSIS

```
# lets look at the Premium customers lifestage stats
lifestage_counts = purchase_df['LIFESTAGE'].value_counts()

lifestage_percentage = purchase_df['LIFESTAGE'].value_counts(normalize=True) * 100

lifestage_summary = pd.DataFrame({'Count': lifestage_counts,
    'Percentage': lifestage_percentage.round(2)})

lifestage_summary.sort_values(by='Count', ascending=False)
```

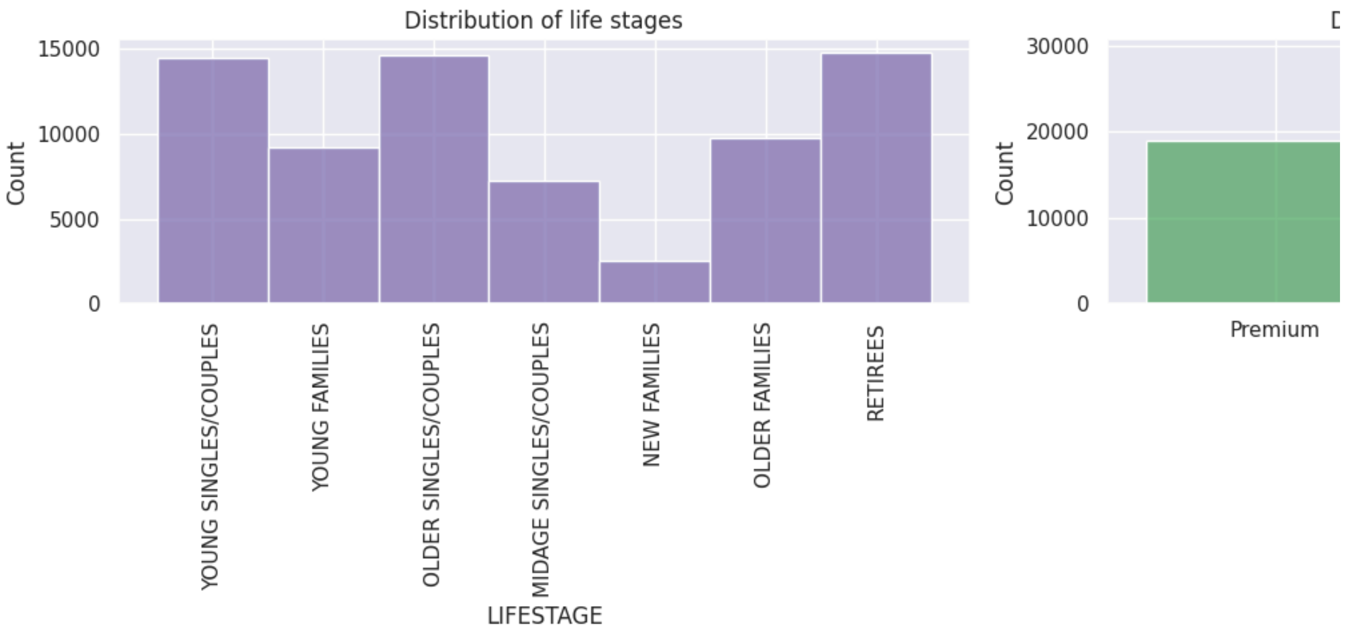
LIFESTAGE	Count	Percentage
RETIREES	14805	20.38
OLDER SINGLES/COUPLES	14609	20.11
YOUNG SINGLES/COUPLES	14441	19.88
OLDER FAMILIES	9780	13.46
YOUNG FAMILIES	9178	12.64
MIDAGE SINGLES/COUPLES	7275	10.02
NEW FAMILIES	2549	3.51

```
# Premium Customer Category Stats
premium_customer_count = purchase_df['PREMIUM_CUSTOMER'].value_counts()

premium_customer_percentage = purchase_df['PREMIUM_CUSTOMER'].value_counts(normalize=True)*100

premium_customer_summary = pd.DataFrame({'PremiumCustomer_Count':premium_customer_count,'PremiumCustomer_Percentage':premiun

premium_customer_summary.sort_values(by='PremiumCustomer_Count',ascending=False)
```

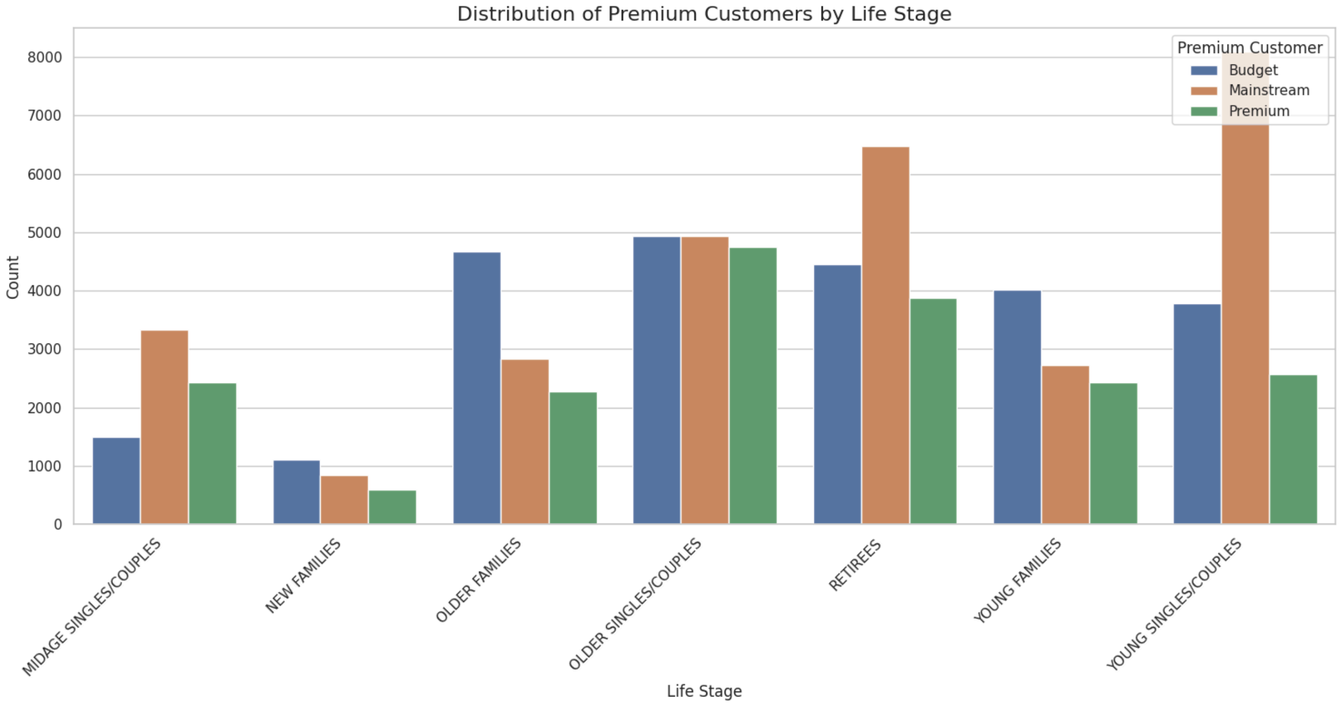
PREMIUM_CUSTOMER	PremiumCustomer_Count	PremiumCustomer_Percentage
Mainstream	29245	40.26
Budget	24470	33.69
Premium	18922	26.05

Premium Mainstream Customer tend be the most with 40.46% of overall Premium Cutsomer category

```
# Frequency bar chart for lifestage
fig, ax = plt.subplots(1, 2, figsize=(15,5))
sns.histplot(
    data = purchase_df,
    x= 'LIFESTAGE',
    ax=ax[0],
    color=sns.color_palette()[4]
)
ax[0].tick_params(axis='x', rotation=90)
ax[0].set_title("Distribution of life stages")

sns.histplot(
    data = purchase_df,
    x= 'PREMIUM_CUSTOMER',
    ax=ax[1],
    color=sns.color_palette()[2]
)
ax[1].set_title("Distribution of customer price points")

fig.tight_layout()
```



```
df_premium_customer = purchase_df.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'])['PREMIUM_CUSTOMER'].count().reset_index(name='C


# Set the figure size and style
plt.figure(figsize=(15, 8))
sns.set_theme(style="whitegrid")

# Create a grouped bar chart
sns.barplot(
    data=df_premium_customer,
    x='LIFESTAGE',
    y='Count',
    hue='PREMIUM_CUSTOMER'
)

# Rotate the x-axis labels for better readability
plt.xticks(rotation=45, ha='right')

# Add titles and labels
plt.title("Distribution of Premium Customers by Life Stage", fontsize=16)
plt.xlabel("Life Stage", fontsize=12)
plt.ylabel("Count", fontsize=12)

# Add legend
plt.legend(title="Premium Customer", loc="upper right")

# Display the plot
plt.tight_layout()
plt.show()
```



Merging two dataframes

```
retail_data = transaction_df.merge(purchase_df, on='LYLTY_CARD_NBR', how='inner')
retail_data.head()
```

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACKET_SIZE	BRAND	MONTH	
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0	175	Natural Chip Co	October	Wednes
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3	175	CCs	May	Tues
2	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9	170	Smiths	May	Mor
3	2018-08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	15.0	175	Smiths	August	Fr
4	2018-08-18	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	13.8	150	Kettle	August	Satu

Exploratoty Data Analysis on Retail Data

```
retail_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 246739 entries, 0 to 246738
Data columns (total 14 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   DATE             246739 non-null  datetime64[ns]
 1   STORE_NBR        246739 non-null  int64
 2   LYLTY_CARD_NBR   246739 non-null  int64
 3   TXN_ID           246739 non-null  int64
 4   PROD_NBR         246739 non-null  int64
 5   PROD_NAME         246739 non-null  object
 6   PROD_QTY          246739 non-null  int64
 7   TOT_SALES         246739 non-null  float64
 8   PACKET_SIZE       246739 non-null  int64
 9   BRAND             246739 non-null  object
 10  MONTH             246739 non-null  object
 11  DAY               246739 non-null  object
 12  LIFESTAGE         246739 non-null  object
 13  PREMIUM_CUSTOMER  246739 non-null  object
dtypes: datetime64[ns](1), float64(1), int64(6), object(6)
memory usage: 26.4+ MB
```

Double-click (or enter) to edit

```
retail_data.duplicated().sum()
```

```
0
```

```
numeric =retail_data[['PROD_QTY','TOT_SALES','PACKET_SIZE']]
```

```
numeric.describe()
```

	PROD_QTY	TOT_SALES	PACKET_SIZE
count	246739.000000	246739.000000	246739.000000
mean	1.906456	7.316118	175.583523
std	0.342500	2.474901	59.432239
min	1.000000	1.700000	70.000000
25%	2.000000	5.800000	150.000000
50%	2.000000	7.400000	170.000000
75%	2.000000	8.800000	175.000000
max	5.000000	29.500000	380.000000

Output Summary

This output provides a comprehensive overview of the distribution and central tendency of the PROD_QTY, TOT_SALES, and Packet_Size variables in the dataset.

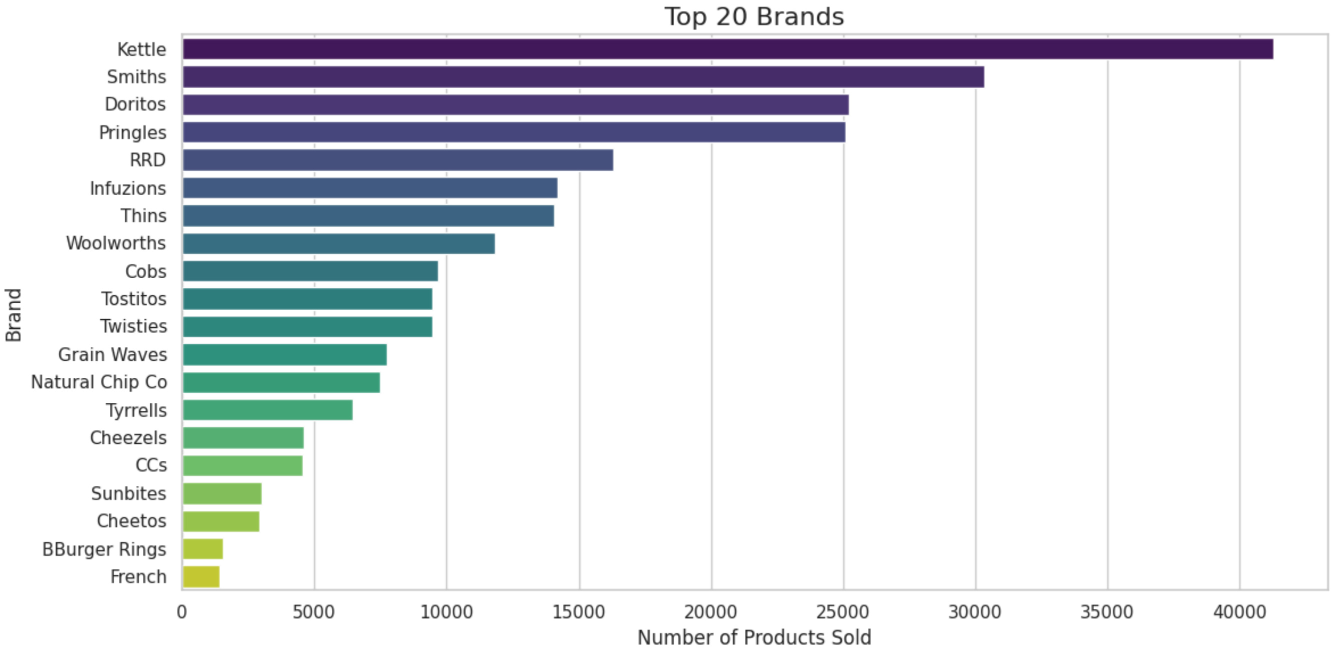
The average product quantity sold per transaction is around 1.91, with most transactions involving 1 to 2 products. Total sales values vary but tend to average around 7.32. The packet sizes range from 70 to 380 grams, with an average of 182.20 grams.

Kettle is the most favorite brand

Double-click (or enter) to edit

```
brand_counts = retail_data['BRAND'].value_counts()

top_brands = brand_counts.head(20)

# Plot the data
plt.figure(figsize=(12, 6))
sns.barplot(x=top_brands.values, y=top_brands.index, palette='viridis')
plt.title('Top 20 Brands', fontsize=16)
plt.xlabel('Number of Products Sold', fontsize=12)
plt.ylabel('Brand', fontsize=12)
plt.tight_layout()
plt.show()
```

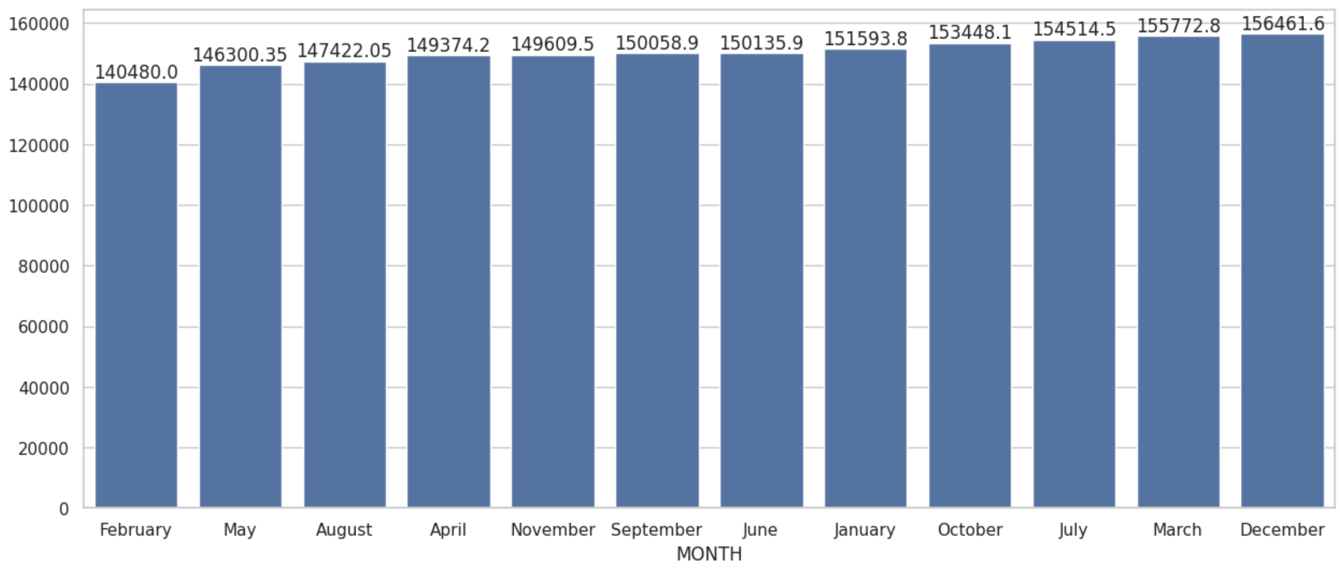
```
<ipython-input-114-ac2983a78a90>:7: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue`

  sns.barplot(x=top_brands.values, y=top_brands.index, palette='viridis')
```



Monthly Sales

- Lowest Sales: February has the lowest total sales, around 140,480.
- Highest Sales: December shows the highest total sales, approximately 156,461.6.
- Consistency: The total sales are relatively consistent across months, with no dramatic spikes or drops.
- Interpretation: This suggests that sales are steady throughout the year, but there might be a slight increase in sales during December (possibly due to holiday shopping). February might have fewer shopping days or lower consumer activity.

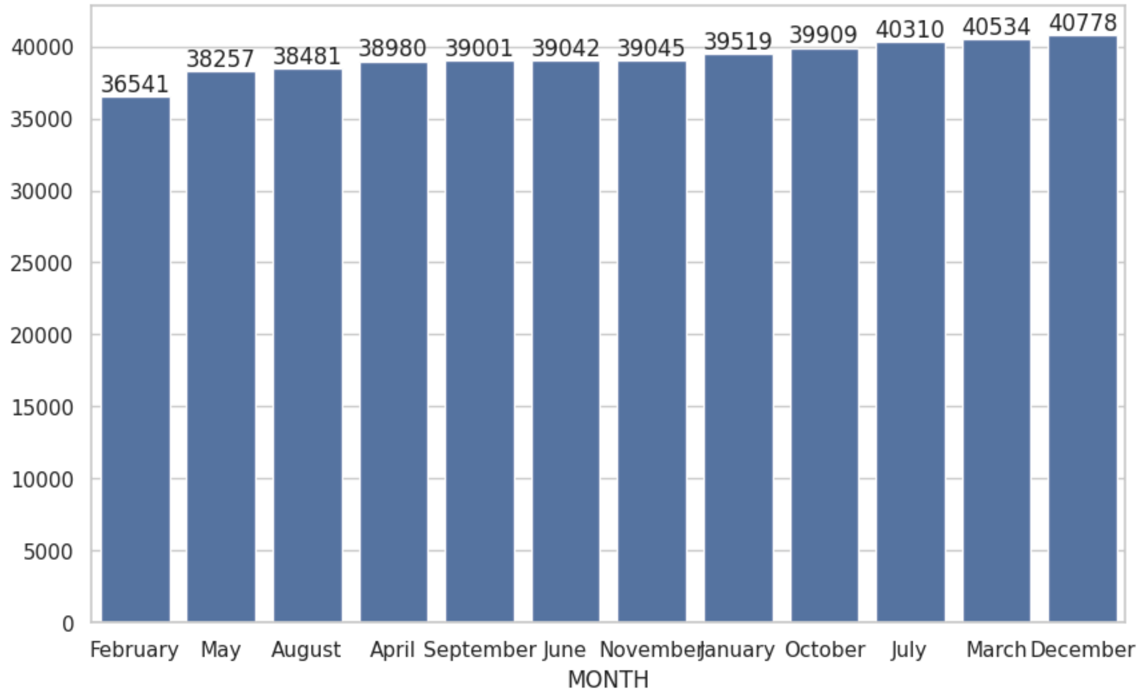
```
#total sales by month
monthly_sales = retail_data.groupby('MONTH')['TOT_SALES'].sum()
#plot monthly sales and sort it ascending
monthly_sales = monthly_sales.sort_values()
plt.figure(figsize=(15, 6))
sns.barplot(x=monthly_sales.index, y=monthly_sales.values)
plt
#show the values on each bar
for i, v in enumerate(monthly_sales.values):
    plt.text(i, v, str(v), ha='center', va='bottom')
```



Monthly Sales Volume

- Lowest Volume: February again has the lowest volume of products sold, with 36,541 units.
- Highest Volume: December has the highest product volume, with 40,778 units sold.
- Consistency: Similar to the sales trend, the product volumes remain steady, with only slight variations across months.
- Interpretation: The product quantity trend aligns with the sales trend, showing that both sales and volume increase slightly in December. February's lower performance in both metrics could be linked to shorter days or reduced consumer activity.

```
#total volume by month
monthly_volume = retail_data.groupby('MONTH')['PROD_QTY'].sum()
#sort the montly volume and plot
monthly_volume = monthly_volume.sort_values()
plt.figure(figsize=(10, 6))
sns.barplot(x=monthly_volume.index, y=monthly_volume.values)
plt
#show the volume at each bar
for i, v in enumerate(monthly_volume.values):
    plt.text(i, v, str(v), ha='center', va='bottom')
```

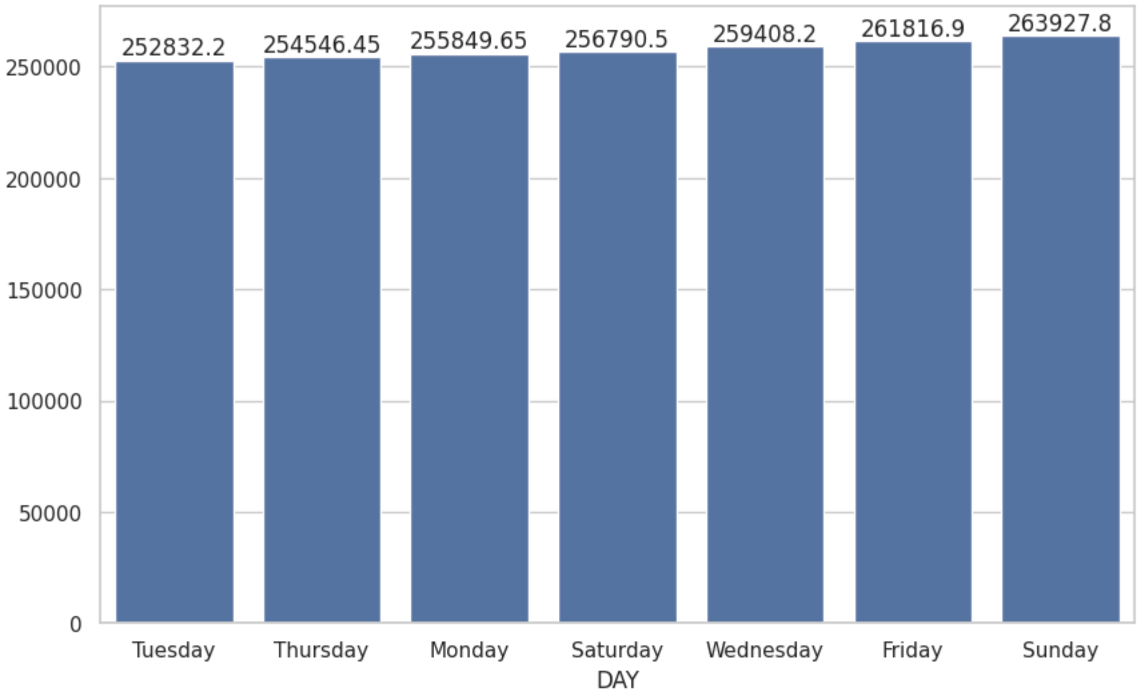


Sales by Day

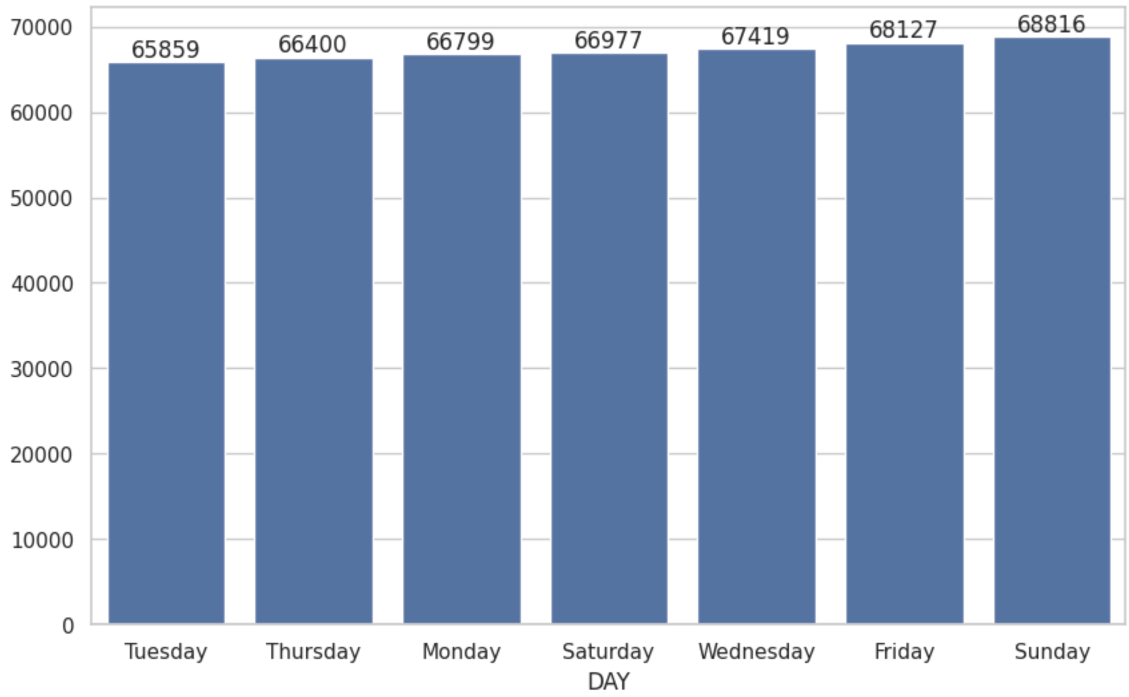
Key Takeaways:

- Lowest Sales: Tuesday has the lowest total sales, amounting to 252,832.2. Highest Sales: Sunday has the highest total sales, reaching 263,927.8. Variation Across Days: The sales figures across all days are relatively close, with only minor differences.
- Interpretation:
  - Weekday vs. Weekend Trend: Sunday and Friday show slightly higher sales, indicating potential increased consumer activity on weekends.
  - Mid-week days (Tuesday and Thursday) appear to have marginally lower sales compared to the weekend.
  - Consistency: Sales remain fairly steady throughout the week, with no drastic dips or spikes, suggesting a stable customer base
- Business Implication: While sales are steady, focusing on weekend promotions (Friday to Sunday) might enhance revenue further since these days already perform slightly better. Investigating the dip on Tuesday may reveal opportunities to boost engagement or implement targeted campaigns

```
# Find the day with the maximum sales
day_sales = retail_data.groupby('DAY')['TOT_SALES'].sum()
day_sales  = day_sales.sort_values()
plt.figure(figsize=(10, 6))
sns.barplot(x=day_sales .index, y=day_sales .values)
plt
##show the total sales at each bar
for i, v in enumerate(day_sales .values):
    plt.text(i, v, str(v), ha='center', va='bottom')
```



```
# Find the day with the maximum sales by volume
day_volume = retail_data.groupby('DAY')['PROD_QTY'].sum()
day_volume  = day_volume.sort_values()
plt.figure(figsize=(10, 6))
sns.barplot(x=day_volume .index, y=day_volume .values)
#show the total sales at each bar
for i, v in enumerate(day_volume .values):
    plt.text(i, v, str(v), ha='center', va='bottom')
```



Snack chips sales are highest in December due to festive celebrations, increased gatherings, and promotional campaigns, while February sees the lowest sales due to post-holiday spending cuts, health resolutions, and fewer social events. Seasonal and behavioral factors, like winter preferences and reduced advertising, also contribute.

SALES AND CUSTOMER BEHAVIOUR ANALYSIS BY LIFESTAGE GROUP

- **High Sales Groups:** "Older Singles/Couples" and "Retirees" drive the majority of sales (over 39% combined), indicating these are key demographics to target.
- **Bulk Buyers:** "Older Families" and "Young Families" purchase more packets per customer on average, making them potential targets for bulk or volume-based promotions.
- **Price Sensitivity:** The average price per unit remains fairly stable across groups, suggesting similar pricing strategies for most customer segments.
- **Opportunities:** Groups like "New Families" and "Young Singles/Couples," which contribute smaller portions of sales, could be targeted with marketing campaigns to increase engagement.

```
# calculate the customer percentage per lifestage
sales_by_LG = retail_data.groupby(['LIFESTAGE'])['TOT_SALES'].sum().reset_index()
sales_by_LG['Percent'] = 100*sales_by_LG['TOT_SALES'] / sales_by_LG['TOT_SALES'].sum()
sales_by_LG['Percent'] = sales_by_LG['Percent'].round(2)
sales_by_LG.sort_values('Percent', ascending=False, inplace=True)

# Add number of customers
cust_count = retail_data.groupby(['LIFESTAGE'])['LYLTY_CARD_NBR'].nunique().reset_index()
sales_by_LG = sales_by_LG.merge(cust_count, how='inner', on=['LIFESTAGE',])

# Add average number of packets bought per customer
avg_qty = retail_data.groupby(['LIFESTAGE', 'LYLTY_CARD_NBR'])['PROD_QTY'].sum().groupby(['LIFESTAGE']).mean().reset_index()
sales_by_LG = sales_by_LG.merge(avg_qty, how='inner', on=['LIFESTAGE'])

# Average price per unit sold
retail_data['unit_price'] = retail_data['TOT_SALES'] / retail_data['PROD_QTY']
avg_price = retail_data.groupby(['LIFESTAGE'])['unit_price'].mean().round(2)
sales_by_LG = sales_by_LG.merge(avg_price, how='inner', on=['LIFESTAGE'])

sales_by_LG.rename(columns={'LYLTY_CARD_NBR':'cust_count', 'PROD_QTY':'avg_qty', 'unit_price':'avg_price'}, inplace=True)
sales_by_LG.sort_values('Percent', ascending=False, inplace=True)
sales_by_LG
```

	LIFESTAGE	TOT_SALES	Percent	cust_count	avg_qty	avg_price
0	OLDER SINGLES/COUPLES	376013.65	20.83	14389	6.75	3.86
1	RETIREES	342381.90	18.97	14555	6.04	3.89
2	OLDER FAMILIES	328519.90	18.20	9630	9.13	3.74
3	YOUNG FAMILIES	294627.90	16.32	9036	8.70	3.75
4	YOUNG SINGLES/COUPLES	243756.60	13.50	14044	4.44	3.89
5	MIDAGE SINGLES/COUPLES	172523.80	9.50	7141	[illegible]	[illegible]

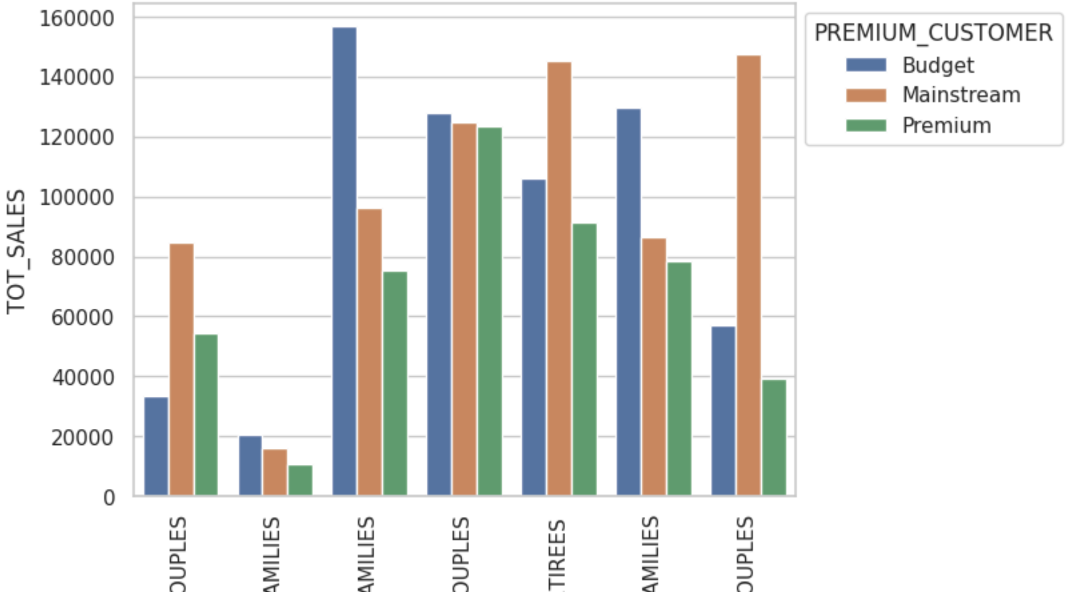
Next Generate code with sales_by_LC View recommended plots New interactive sheet

Sales Performance Analysis Across Lifestages and Customer Segments

- Older Families and Retirees are key customers:Older Families, particularly in the Budget category, make significant contributions to sales and purchase large quantities, showing strong demand and loyalty.
- Retirees also exhibit consistent buying behavior, with a focus on Budget and Mainstream products.
- Young Singles/Couples are price-sensitive: Despite having a high number of customers, the average price paid per unit is higher for Mainstream customers but lower for Budget customers. This shows variation in product preferences.
- Premium Segments are niche but valuable: While Premium customers represent smaller segments, their purchases tend to skew toward higher unit prices.
- New Families are a low-engagement segment: They have the lowest total sales and customer counts, indicating potential for targeted marketing or product offerings to increase their engagement.

```
# Total sales by lifestage and premium_customeror

sales_by_segment = retail_data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'])['TOT_SALES'].sum().reset_index()

g=sns.barplot(
    data = sales_by_segment,
    x='LIFESTAGE',
    y='TOT_SALES',
    hue='PREMIUM_CUSTOMER'
)
sns.move_legend(g, "upper left", bbox_to_anchor=(1, 1))
plt.xticks(rotation=90)
```

```
([0, 1, 2, 3, 4, 5, 6],
 [Text(0, 0, 'MIDAGE SINGLES/COUPLES'),
  Text(1, 0, 'NEW FAMILIES'),
  Text(2, 0, 'OLDER FAMILIES'),
  Text(3, 0, 'OLDER SINGLES/COUPLES'),
  Text(4, 0, 'RETIREES'),
  Text(5, 0, 'YOUNG FAMILIES'),
  Text(6, 0, 'YOUNG SINGLES/COUPLES')])
```


TOT_SALES
OUPLES
AMILIES
AMILIES
OUPLES
TIREES
AMILIES
OUPLES
PREMIUM_CUSTOMER
Budget
Mainstream
Premium