quantium

September 7, 2024

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
purchases_df = pd.read_csv('E:/Quantium Internship/QVI_purchase_behaviour.csv')
purchases_df.head()
```

[2]:
```
   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
```

[3]:
```
transactions_df = pd.read_excel('E:/Quantium Internship/QVI_transaction_data.
 ↪xlsx')
transactions_df.head()
```

[3]:
```
    DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
0  43390          1            1000       1         5
1  43599          1            1307     348        66
2  43605          1            1343     383        61
3  43329          2            2373     974        69
4  43330          2            2426    1038       108

                                  PROD_NAME  PROD_QTY  TOT_SALES
0    Natural Chip        Compny SeaSalt175g         2        6.0
1                  CCs Nacho Cheese    175g         3        6.3
2    Smiths Crinkle Cut  Chips Chicken 170g         2        2.9
3    Smiths Chip Thinly  S/Cream&Onion 175g         5       15.0
4  Kettle Tortilla ChpsHny&Jlpno Chili 150g         3       13.8
```

[4]:
```
print(f'null values in purchases_df: {purchases_df.isnull().sum().sum()}')
print(f'null values in transactions_df: {transactions_df.isnull().sum().sum()}')
print(f'number of duplicated rows in purchases_df: {purchases_df.duplicated().
 ↪sum()}')
print(f'number of duplicated rows in transactions_df: {transactions_df.
 ↪duplicated().sum()}')
```

```
transactions_df.drop_duplicates(inplace=True, keep='first')
print(f'number of duplicated rows in transactions_df after droping duplicates:␣
  ↪{transactions_df.duplicated().sum()}')
```

```
null values in purchases_df: 0
null values in transactions_df: 0
number of duplicated rows in purchases_df: 0
number of duplicated rows in transactions_df: 1
number of duplicated rows in transactions_df after droping duplicates: 0
```

[5]:
```
transactions_df['DATE'] = pd.to_datetime(transactions_df['DATE'],␣
  ↪origin='1899-12-30', unit='D')
```

[6]:
```
merged_df = pd.merge(transactions_df, purchases_df, on='LYLTY_CARD_NBR',␣
  ↪how='left')
print(transactions_df.shape, purchases_df.shape, merged_df.shape)
```

```
(264835, 8) (72637, 3) (264835, 10)
```

[7]:
```
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264835 entries, 0 to 264834
Data columns (total 10 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   DATE              264835 non-null  datetime64[ns]
 1   STORE_NBR         264835 non-null  int64
 2   LYLTY_CARD_NBR    264835 non-null  int64
 3   TXN_ID            264835 non-null  int64
 4   PROD_NBR          264835 non-null  int64
 5   PROD_NAME         264835 non-null  object
 6   PROD_QTY          264835 non-null  int64
 7   TOT_SALES         264835 non-null  float64
 8   LIFESTAGE         264835 non-null  object
 9   PREMIUM_CUSTOMER  264835 non-null  object
dtypes: datetime64[ns](1), float64(1), int64(5), object(3)
memory usage: 20.2+ MB
```

[8]:
```
# looking for outliers
extremely_large_transactions = merged_df.loc[merged_df['PROD_QTY'] > 5]
print(f'number of extreme values: {extremely_large_transactions.shape[0]}')
clean_df = merged_df.drop(extremely_large_transactions.index)
clean_df['PACK_SIZE'] = clean_df['PROD_NAME'].str.extract(r'(\d+)').
  ↪astype('int')
```

```
number of extreme values: 2
```

[9]:
```
clean_df['BRAND'] = clean_df['PROD_NAME'].str.split().str[0]
```

[10]:

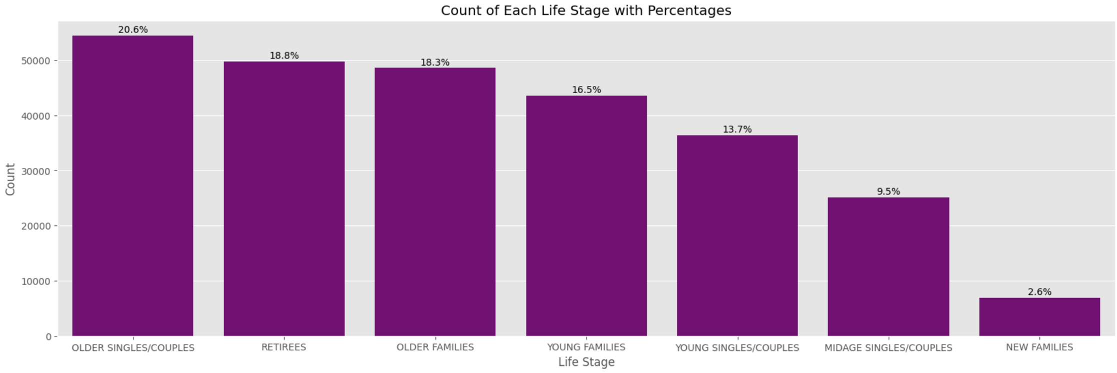
```
clean_df[['PROD_QTY', 'TOT_SALES']].describe()
```

[10]:

```
            PROD_QTY      TOT_SALES
count  264833.000000  264833.000000
mean        1.905812       7.299351
std         0.343437       2.527244
min         1.000000       1.500000
25%         2.000000       5.400000
50%         2.000000       7.400000
75%         2.000000       9.200000
max         5.000000      29.500000
```

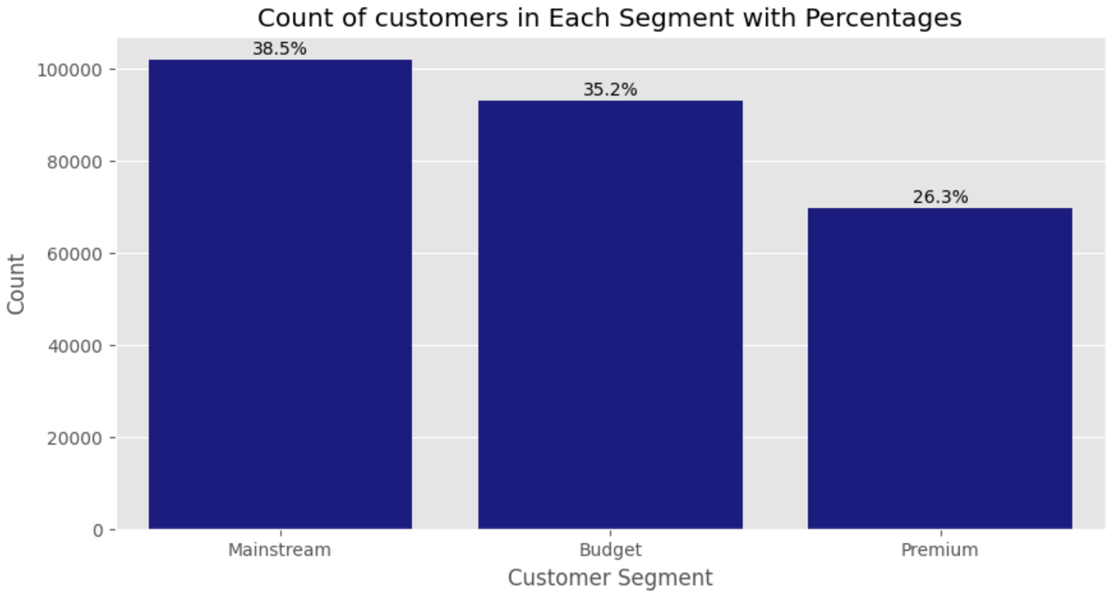
[11]:

```
# Customer Lifestage segmentation
plt.style.use('ggplot')
plt.figure(figsize=(20, 6))
ax = sns.countplot(x='LIFESTAGE', data=clean_df, order=clean_df['LIFESTAGE'].
 ↪value_counts().index, color='purple')

# Calculating the percentages
total = len(clean_df)
for p in ax.patches:
    percentage = '{:.1f}%'.format(100 * p.get_height() / total)
    x = p.get_x() + p.get_width() / 2
    y = p.get_height() + 0.002 * total
    ax.text(x, y, percentage, ha='center', size=10)

# Customizing the plot
plt.xticks(size=10)
plt.title('Count of Each Life Stage with Percentages')
plt.xlabel('Life Stage')
plt.ylabel('Count')
plt.show()
```



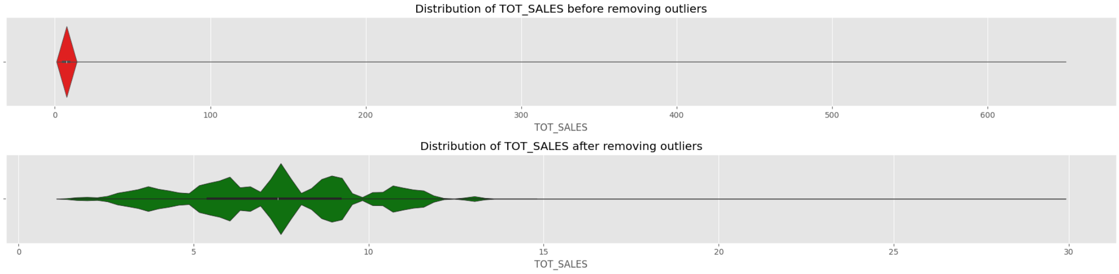
[12]:

```
# Customer type segmentation
plt.figure(figsize=(10, 5))
g = sns.countplot(x='PREMIUM_CUSTOMER', data=clean_df,␣
 ↪order=clean_df['PREMIUM_CUSTOMER'].value_counts().index, color='darkblue',␣
 ↪alpha=0.95)

# Calculating the percentages
total = len(clean_df)
for p in g.patches:
    percentage = '{:.1f}%'.format(100 * p.get_height() / total)
    x = p.get_x() + p.get_width() / 2
    y = p.get_height() + 0.005 * total
    g.text(x, y, percentage, ha='center', size=10)
g.set_title('Count of customers in Each Segment with Percentages')
plt.xlabel('Customer Segment')
plt.ylabel('Count')
plt.show()
```



[13]:

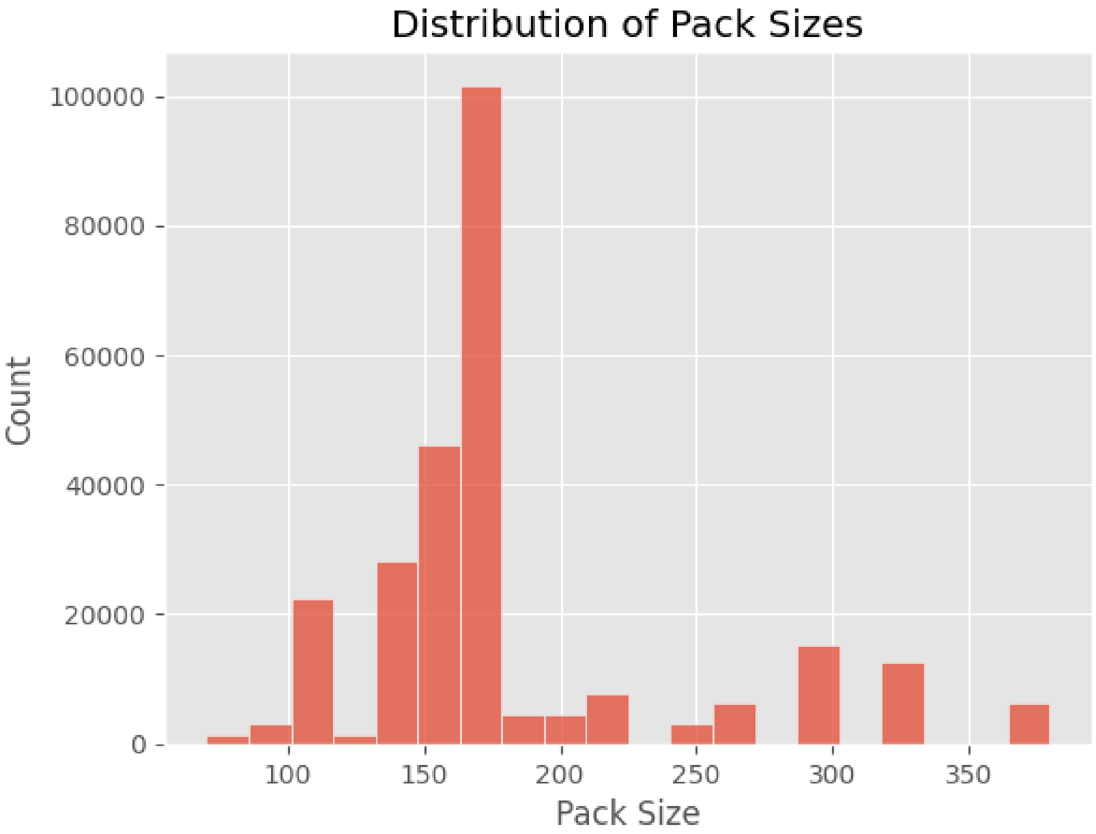
```
# Distribution of TOT_SALES before and after removing outliers
fig, ax = plt.subplots(2, 1, figsize=(20, 5))
sns.violinplot(x='TOT_SALES', data=merged_df, ax=ax[0], color='red')
sns.violinplot(x='TOT_SALES', data=clean_df, ax=ax[1], color='green')
ax[0].set_title('Distribution of TOT_SALES before removing outliers')
ax[1].set_title('Distribution of TOT_SALES after removing outliers')
plt.tight_layout()
plt.show()
```


Distribution of TOT_SALES before removing outliers

Distribution of TOT_SALES after removing outliers

[14]:

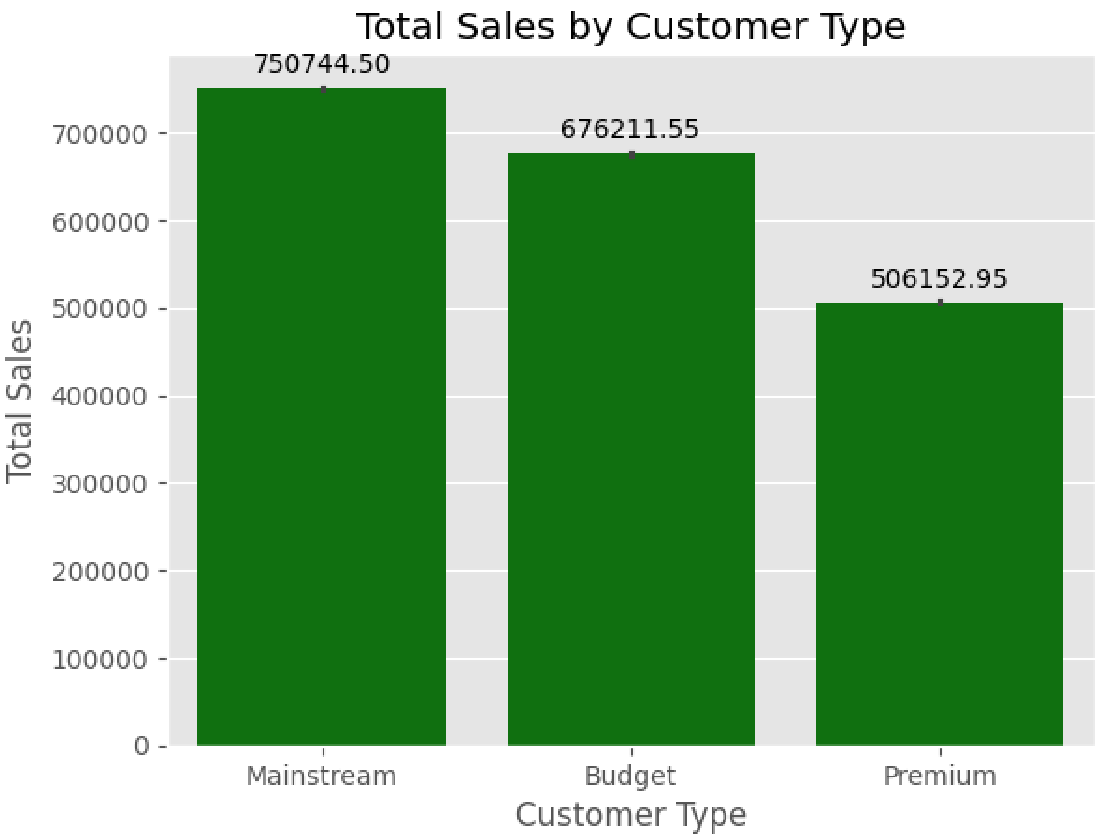
```
# Distribution of pack sizes
sns.histplot(x='PACK_SIZE', data=clean_df, bins=20)
plt.title('Distribution of Pack Sizes')
plt.xlabel('Pack Size')
plt.ylabel('Count')
plt.show()
```


Distribution of Pack Sizes

[15]:

```
# Total sales grouped by customer type
```

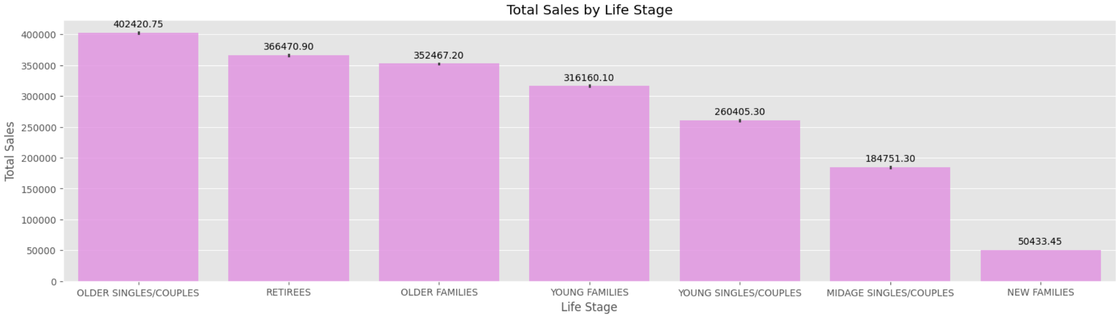
```
g = sns.barplot(x='PREMIUM_CUSTOMER', y='TOT_SALES', data=clean_df, estimator=sum, order=clean_df.groupby('PREMIUM_CUSTOMER')['TOT_SALES'].sum().sort_values(ascending=False).index, color='green')
for p in g.patches:
    g.annotate(format(p.get_height(), '.2f'),
               (p.get_x() + p.get_width() / 2., p.get_height()),
               ha = 'center', va = 'center',
               xytext = (0, 9),
               textcoords = 'offset points')
g.set_title('Total Sales by Customer Type')
plt.xlabel('Customer Type')
plt.ylabel('Total Sales')
plt.show()
```



[16]:

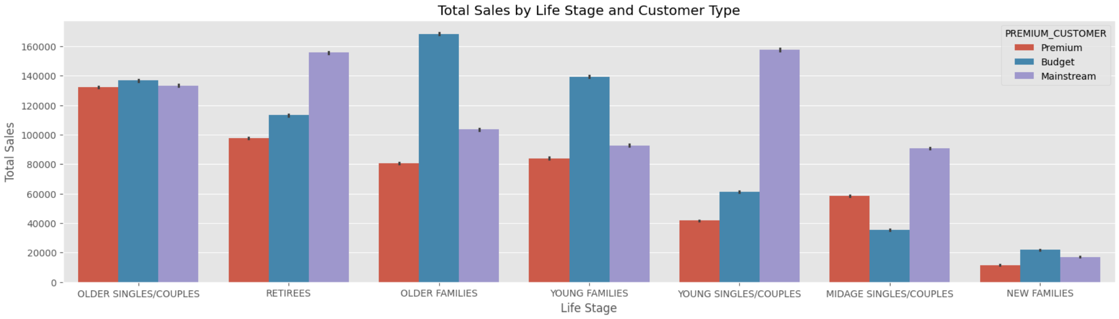
```
# Total sales grouped by lifestage
fig, ax = fig, ax = plt.subplots(figsize=(20, 5))
sns.barplot(x='LIFESTAGE', y='TOT_SALES', estimator=sum, order=clean_df.groupby('LIFESTAGE')['TOT_SALES'].sum().sort_values(ascending=False).index, data=clean_df, color='violet', alpha=0.8)
```

```
# Annotate the bars
for p in ax.patches:
    ax.annotate(format(p.get_height(), '.2f'),
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center',
                xytext=(0, 9),
                textcoords='offset points')

# Customize the plot
plt.title('Total Sales by Life Stage')
plt.xlabel('Life Stage')
plt.ylabel('Total Sales')
plt.show()
```



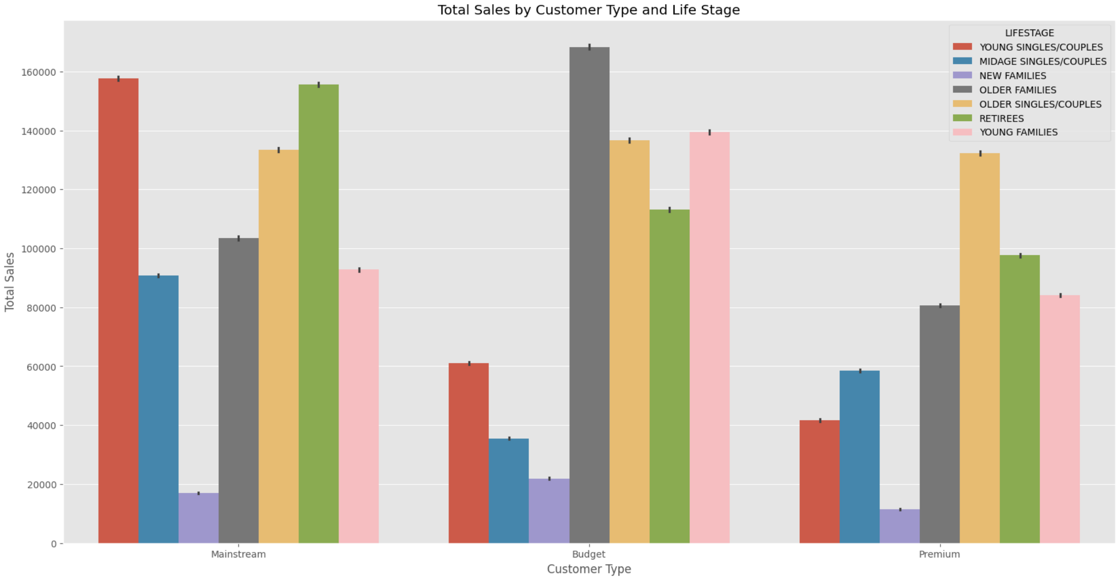
[17]:

```
# Total sales grouped by lifestage and customer type
plt.figure(figsize=(20, 5))
sns.barplot(x='LIFESTAGE', y='TOT_SALES', estimator=sum, order=clean_df.
 ↪groupby('LIFESTAGE')['TOT_SALES'].sum().sort_values(ascending=False).index,␣
 ↪hue='PREMIUM_CUSTOMER', data=clean_df)
plt.title('Total Sales by Life Stage and Customer Type')
plt.xlabel('Life Stage')
plt.ylabel('Total Sales')
plt.show()
```



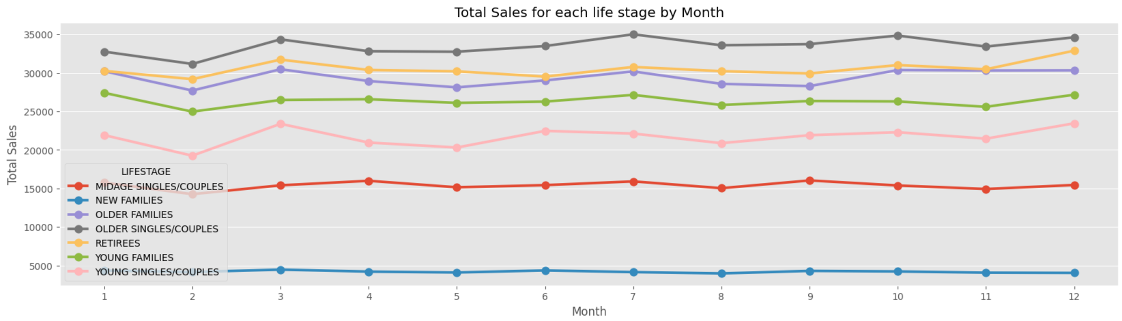
[18]:

```
# Total sales grouped by customer type and lifestage
plt.figure(figsize=(20, 10))
sns.barplot(x='PREMIUM_CUSTOMER', y='TOT_SALES', estimator=sum, order=clean_df.
 ↪groupby('PREMIUM_CUSTOMER')['TOT_SALES'].sum().sort_values(ascending=False).
 ↪index, hue='LIFESTAGE', data=clean_df)
plt.title('Total Sales by Customer Type and Life Stage')
plt.xlabel('Customer Type')
plt.ylabel('Total Sales')
plt.show()
```



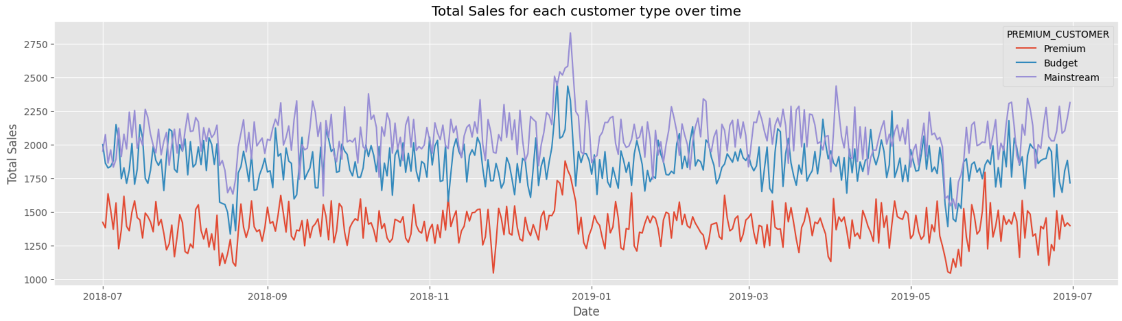
[19]:

```
# Total sales by month for each life stage
clean_df['MONTH'] = clean_df['DATE'].dt.month
plt.figure(figsize=(20, 5))
sns.pointplot(x='MONTH', y='TOT_SALES', estimator=sum, data=clean_df,␣
 ↪hue='LIFESTAGE', errorbar=None)
plt.title('Total Sales for each life stage by Month')
plt.xlabel('Month')
plt.ylabel('Total Sales')
plt.show()
```



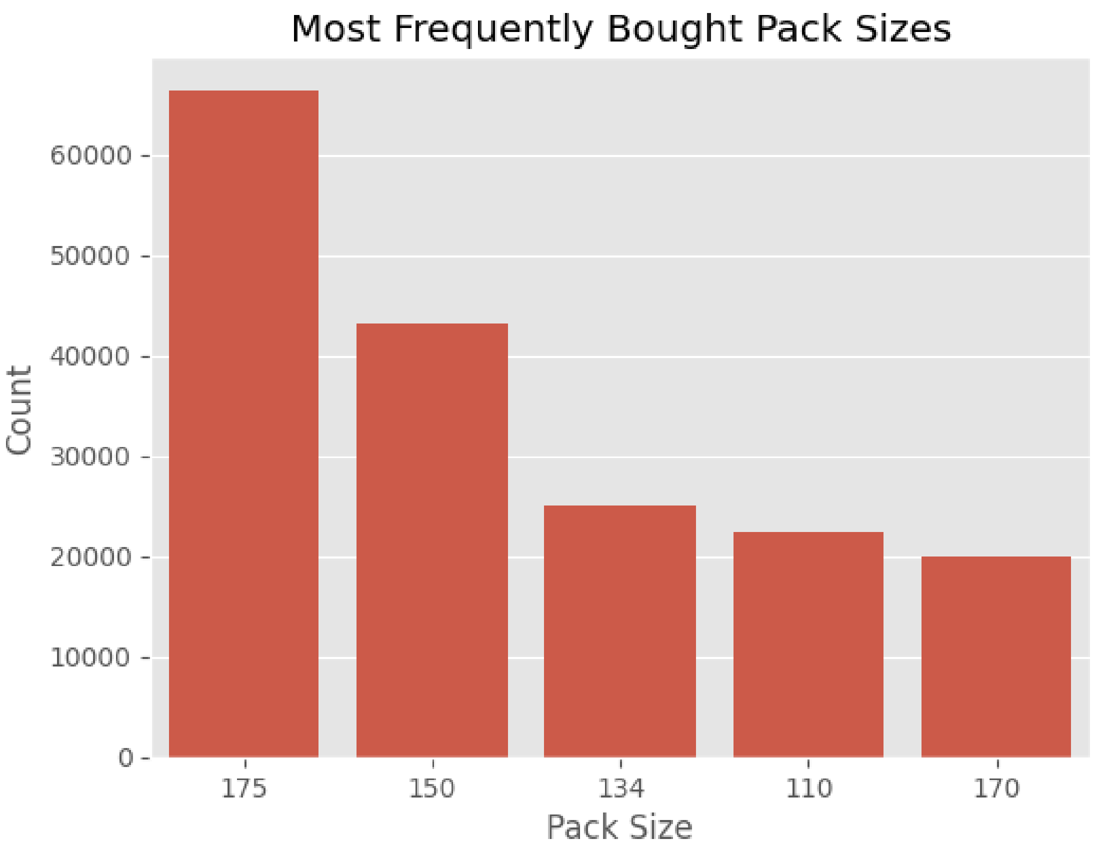
[20]:

```
# Total Sales for each customer type over time
plt.figure(figsize=(20, 5))
sns.lineplot(x='DATE', y='TOT_SALES', data=clean_df, errorbar=None,␣
 ↪hue='PREMIUM_CUSTOMER', estimator=sum)
plt.title('Total Sales for each customer type over time')
plt.xlabel('Date')
plt.ylabel('Total Sales')
plt.show()
```

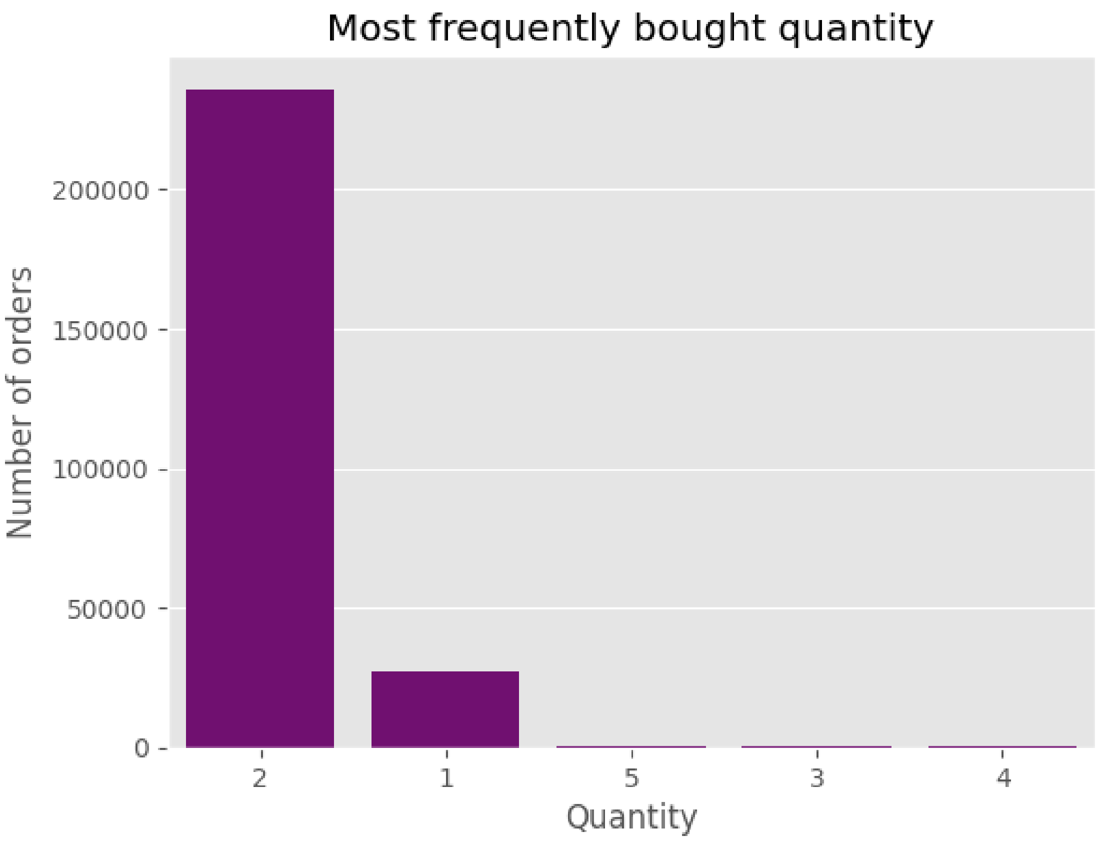


[21]:

```
# Most frequently bought pack sizes
sns.countplot(x='PACK_SIZE', data=clean_df, order=clean_df['PACK_SIZE'].
 ↪value_counts().index[:5])
plt.title('Most Frequently Bought Pack Sizes')
plt.xlabel('Pack Size')
plt.ylabel('Count')
plt.show()
```

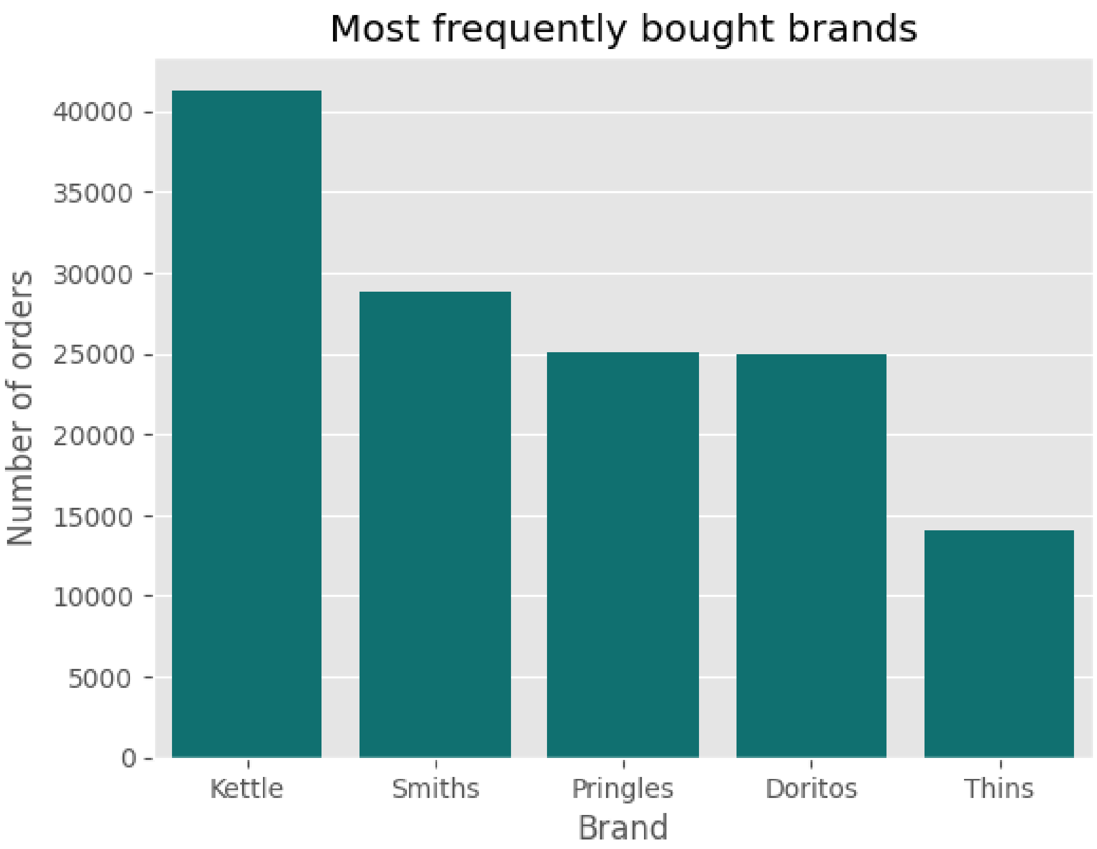


[22]:
```
# Most usually bought quantity
sns.countplot(x='PROD_QTY', data=clean_df, order=clean_df['PROD_QTY'].
 ↪value_counts().index, color='purple')
plt.title('Most frequently bought quantity')
plt.xlabel('Quantity')
plt.ylabel('Number of orders')
plt.show()
```

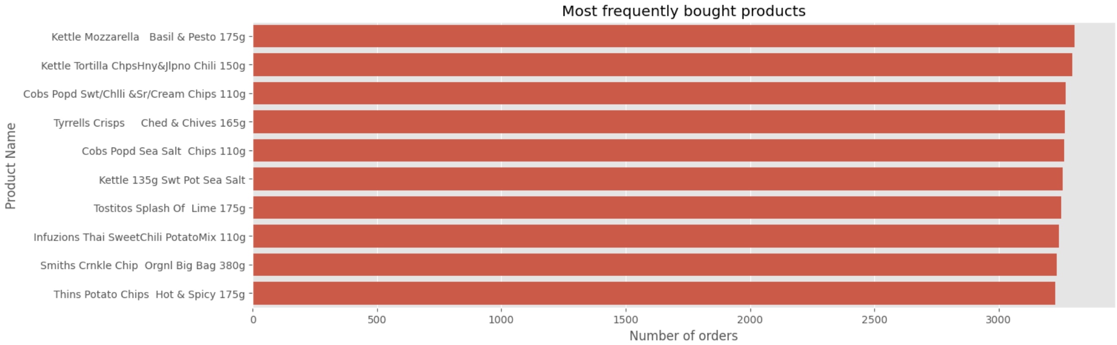


[23]:

```
# Most frequently bought brands
sns.countplot(x='BRAND', data=clean_df, order=clean_df['BRAND'].value_counts().
  ↪index[:5], color='teal')
plt.title('Most frequently bought brands')
plt.xlabel('Brand')
plt.ylabel('Number of orders')
plt.show()
```

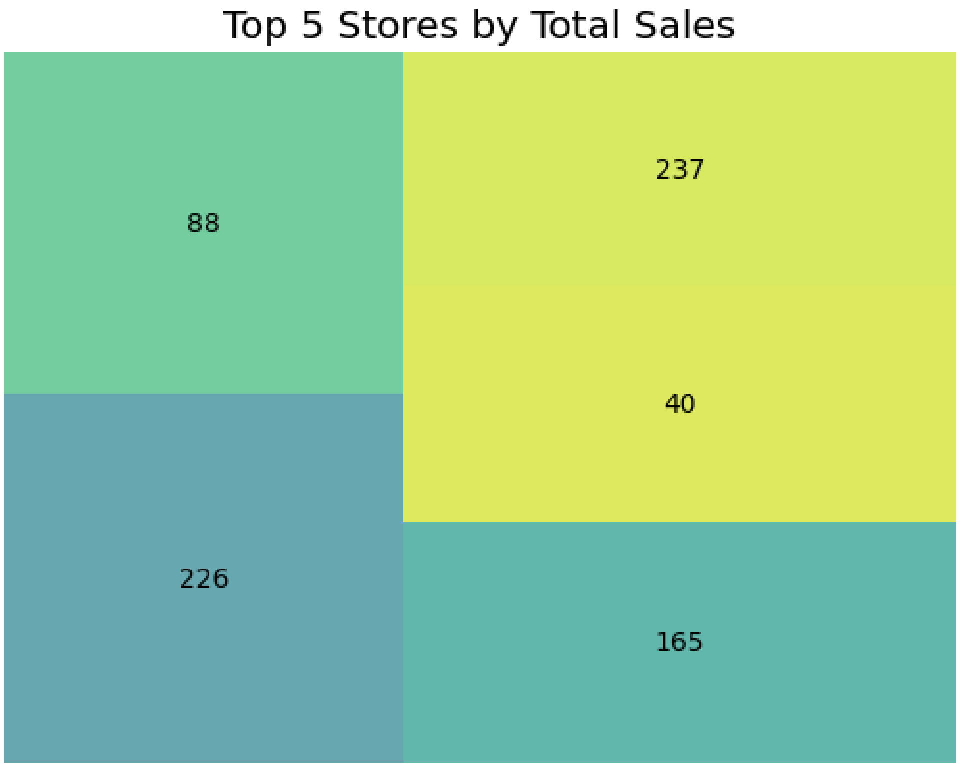


[24]:
```
# Most frequently bought products
plt.figure(figsize=(15, 5))
sns.countplot(y='PROD_NAME', data=clean_df, order=clean_df['PROD_NAME'].
 ↪value_counts().index[:10])
plt.title('Most frequently bought products')
plt.xlabel('Number of orders')
plt.ylabel('Product Name')
plt.show()
```



[25]:

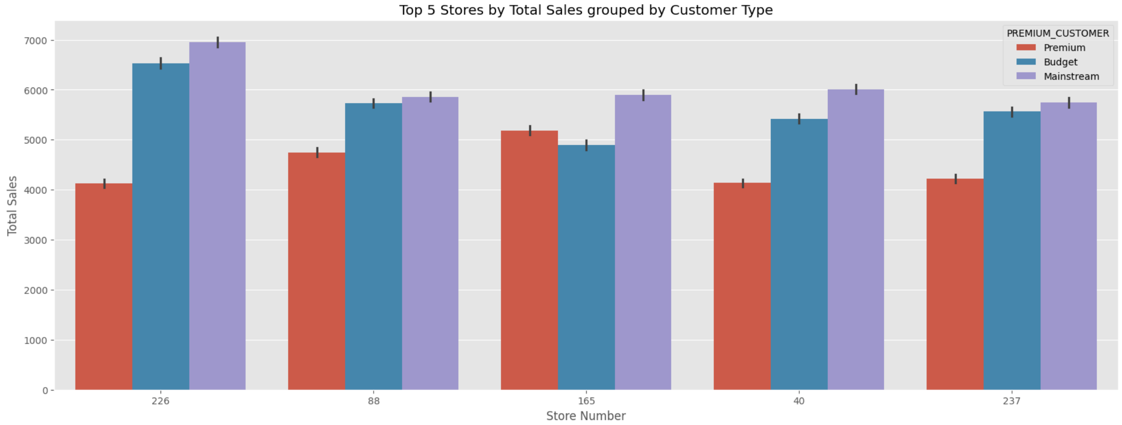
```
# Top 10 stores with the highest total sales
# plt.figure(figsize=(20, 5))
# sns.barplot(x='STORE_NBR', y='TOT_SALES', data=clean_df, estimator=sum,␣
 ↪order=clean_df.groupby('STORE_NBR')['TOT_SALES'].sum().
 ↪sort_values(ascending=False).index[:10], color='green', alpha=0.8)

import squarify

top_10_stores = clean_df.groupby('STORE_NBR')['TOT_SALES'].sum().
 ↪sort_values(ascending=False).head(5)
squarify.plot(sizes=top_10_stores, label=top_10_stores.index, alpha=0.7)
plt.title('Top 5 Stores by Total Sales')
plt.axis('off')
plt.show()
```



[26]:

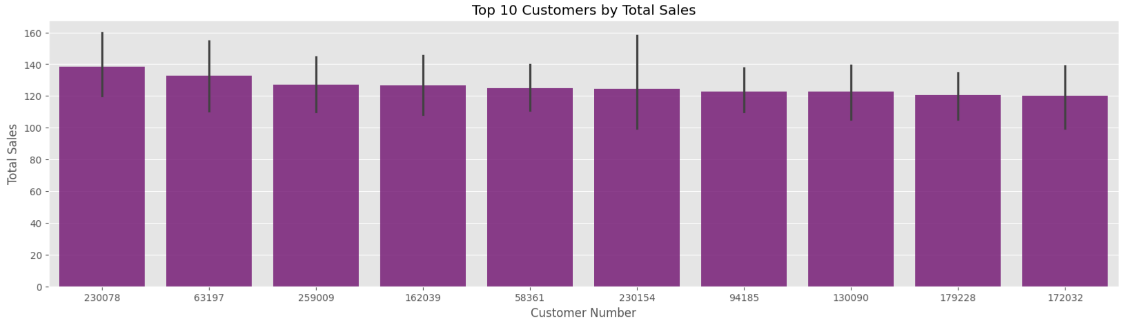
```
# Top 5 stores with the highest total sales grouped by customer type
plt.figure(figsize=(20, 7))
sns.barplot(x='STORE_NBR', y='TOT_SALES', data=clean_df, estimator=sum,␣
 ↪order=clean_df.groupby('STORE_NBR')['TOT_SALES'].sum().
 ↪sort_values(ascending=False).index[:5], hue='PREMIUM_CUSTOMER')
```

```python
plt.title('Top 5 Stores by Total Sales grouped by Customer Type')
plt.xlabel('Store Number')
plt.ylabel('Total Sales')
plt.show()
# We can see that unlike most stores, store 165 has a higher sales from premium customers than budget customers
```



[27]:

```python
# Top 10 customers with the highest total sales
plt.figure(figsize=(20, 5))
sns.barplot(x='LYLTY_CARD_NBR', y='TOT_SALES', data=clean_df, estimator=sum, order=clean_df.groupby('LYLTY_CARD_NBR')['TOT_SALES'].sum().sort_values(ascending=False).index[:10], color='purple', alpha=0.8)
plt.title('Top 10 Customers by Total Sales')
plt.xlabel('Customer Number')
plt.ylabel('Total Sales')
plt.show()
```



[28]:

```python
# clean_df.to_csv('E:/Quantium Internship/final_df.csv', index=False)
```

1 Conclusions:

After completing the analysis we notice some trends in purchasing behaviour, products in demand, customer segments. - The *Older singles/couples* is the largest *Lifestage* segment. - The *Mainstream* is the largest *PREMIUM_CUSTOMER* segment. - The most frequently bought *Pack size* is *175*. - The *Mainstream* segment is one with the heighest *Total Sales* among other *Premuim customer* segments. - The *Older singles/couples* segment is the one with heighest *Total Sales* among other *Lifestage* segments. - The *Midage singles/couples* segment has significantly higher premium customers than budget customers. - The largest portion of our customers are multipack buyers, with 2 units as the most frequently bought quantity. - The most popular *Brand* is *Kettle*. - Store number 226 is the one that generated the heighest *Total Sales*. - The customer with *Loyalty Number* 230078 is the one with heighest *Total Sales*.

2 Business metric:

I suggest using total monthly sales as the main performance indicator

3 Recommendations:

I think the following measures will help increase the total sales: - Create a loyalty program for our most active customers. - Create a marketing strategy targeting (Mainstream customers that belong to the Older singles/couples lifestage) as it's the intersection between our two most active segments. - Create a marketing strategy targeting our least active segments but with discounts and hot offers to incentivize them and generate further sales.