What to do

Start performing high-level data checks such as:

Creating and interpreting high-level summaries of the data Finding outliers and removing these (if applicable) Checking data formats and correcting (if applicable)

First we import libraries, pandas

```
import pandas as pd
import numpy as np
import os
```

We will import the purchase behavior file to clean it

```
purchase_behaviour_df = pd.read_csv("QVI_purchase_behaviour.csv")

purchase_behaviour_df.head()
```

```
                LYLTY_CARD_NBR                LIFESTAGE
PREMIUM_CUSTOMER
LYLTY_CARD_NBR

1000                      1000   YOUNG SINGLES/COUPLES
Premium
1002                      1002   YOUNG SINGLES/COUPLES
Mainstream
1003                      1003           YOUNG FAMILIES
Budget
1004                      1004   OLDER SINGLES/COUPLES
Mainstream
1005                      1005  MIDAGE SINGLES/COUPLES
Mainstream
```

First problem we come across:

We have two indexes, so we need to set the LYLTY_CARD_NBR column to be the index so that we don't get confusing results.

```
purchase_behaviour_df =
purchase_behaviour_df.set_index("LYLTY_CARD_NBR", drop=True)
```

Then again we take a look to see the result

```
purchase_behaviour_df.head()
```

```
                                LIFESTAGE PREMIUM_CUSTOMER
LYLTY_CARD_NBR
1000               YOUNG SINGLES/COUPLES          Premium
1002               YOUNG SINGLES/COUPLES       Mainstream
1003                     YOUNG FAMILIES           Budget
1004               OLDER SINGLES/COUPLES       Mainstream
1005              MIDAGE SINGLES/COUPLES       Mainstream
```

```
purchase_behaviour_df.shape
```

```
(72637, 2)
```

```
purchase_behaviour_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 72637 entries, 1000 to 2373711
Data columns (total 2 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   LIFESTAGE         72637 non-null  object
 1   PREMIUM_CUSTOMER  72637 non-null  object
dtypes: object(2)
memory usage: 1.7+ MB
```

So far we found no missing or inconsistent values.

Next we import the transaction data file to inspect and clean it

```
transaction_data_df = pd.read_excel("QVI_transaction_data.xlsx")
transaction_data_df.head()
```

```
    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
```

```
transaction_data_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
```

First we notice that there're no null data

Secondly the problem we encounter with this dataset is the datatype in the column "DATE"

```
transaction_data_df["DATE"] =
pd.to_datetime(transaction_data_df["DATE"], origin='1899-12-30',
unit='D')

---------------------------------------------------------------------
-----
ValueError                                Traceback (most recent call
last)
Cell In[53], line 1
----> 1 transaction_data_df["DATE"] =
pd.to_datetime(transaction_data_df["DATE"], origin='1899-12-30',
unit='D')

File c:\Users\moham\AppData\Local\Programs\Python\Python313\Lib\site-
packages\pandas\core\tools\datetimes.py:1041, in to_datetime(arg,
errors, dayfirst, yearfirst, utc, format, exact, unit,
infer_datetime_format, origin, cache)
   1038     return None
   1040 if origin != "unix":
-> 1041     arg = _adjust_to_origin(arg, origin, unit)
   1043 convert_listlike = partial(
   1044     _convert_listlike_datetimes,
   1045     utc=utc,
   (...)
   1050     exact=exact,
   1051 )
```

```
   1052 # pylint: disable-next=used-before-assignment

File c:\Users\moham\AppData\Local\Programs\Python\Python313\Lib\site-
packages\pandas\core\tools\datetimes.py:592, in _adjust_to_origin(arg,
origin, unit)
    587 else:
    588     # arg must be numeric
    589     if not (
    590         (is_integer(arg) or is_float(arg)) or
is_numeric_dtype(np.asarray(arg))
    591     ):
--> 592         raise ValueError(
    593             f"'{arg}' is not compatible with
origin='{origin}'; "
    594             "it must be numeric with a unit specified"
    595         )
    597     # we are going to offset back to unix / epoch time
    598     try:

ValueError: '0        2018-10-17
1        2019-05-14
2        2019-05-20
3        2018-08-17
4        2018-08-18
            ...
264831   2019-03-09
264832   2018-08-13
264833   2018-11-06
264834   2018-12-27
264835   2018-09-22
Name: DATE, Length: 264836, dtype: datetime64[ns]' is not compatible
with origin='1899-12-30'; it must be numeric with a unit specified

transaction_data_df.head()

        DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
0 2018-10-17          1            1000       1         5
1 2019-05-14          1            1307     348        66
2 2019-05-20          1            1343     383        61
3 2018-08-17          2            2373     974        69
4 2018-08-18          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

transaction_data_df.describe()
```

```
                                DATE     STORE_NBR  LYLTY_CARD_NBR  \
count                         264836  264836.00000    2.648360e+05
mean   2018-12-30 00:52:12.879215616     135.08011    1.355495e+05
min              2018-07-01 00:00:00       1.00000    1.000000e+03
25%              2018-09-30 00:00:00      70.00000    7.002100e+04
50%              2018-12-30 00:00:00     130.00000    1.303575e+05
75%              2019-03-31 00:00:00     203.00000    2.030942e+05
max              2019-06-30 00:00:00     272.00000    2.373711e+06
std                              NaN      76.78418    8.057998e+04

             TXN_ID       PROD_NBR       PROD_QTY      TOT_SALES
count  2.648360e+05  264836.000000  264836.000000  264836.000000
mean   1.351583e+05      56.583157       1.907309       7.304200
min    1.000000e+00       1.000000       1.000000       1.500000
25%    6.760150e+04      28.000000       2.000000       5.400000
50%    1.351375e+05      56.000000       2.000000       7.400000
75%    2.027012e+05      85.000000       2.000000       9.200000
max    2.415841e+06     114.000000     200.000000     650.000000
std    7.813303e+04      32.826638       0.643654       3.083226
```

Then we will merge the two dataframes on the "LYLTY_CARD_NBR" column

```
sales_behavior = pd.merge(transaction_data_df, purchase_behaviour_df,
on="LYLTY_CARD_NBR")
sales_behavior.head()
```

```
        DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
0 2018-10-17          1            1000       1         5
1 2019-05-14          1            1307     348        66
2 2019-05-20          1            1343     383        61
3 2018-08-17          2            2373     974        69
4 2018-08-18          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

                LIFESTAGE PREMIUM_CUSTOMER
0   YOUNG SINGLES/COUPLES          Premium
1  MIDAGE SINGLES/COUPLES           Budget
2  MIDAGE SINGLES/COUPLES           Budget
3  MIDAGE SINGLES/COUPLES           Budget
4  MIDAGE SINGLES/COUPLES           Budget
```

Then at last we export the data to a new file to protect the original files from being changed.

```
sales_behavior.to_csv("sales_behavior.csv")
```

There are no more problems with the data, so we move on to the analysis part.

First we read the new file

```
import pandas as pd
import numpy as np
sales_behavior_df = pd.read_csv("sales_behavior.csv", index_col=0)

sales_behavior_df.describe()
```

```
          STORE_NBR  LYLTY_CARD_NBR        TXN_ID       PROD_NBR  \
count  264836.00000    2.648360e+05  2.648360e+05  264836.000000
mean      135.08011    1.355495e+05  1.351583e+05      56.583157
std        76.78418    8.057998e+04  7.813303e+04      32.826638
min         1.00000    1.000000e+03  1.000000e+00       1.000000
25%        70.00000    7.002100e+04  6.760150e+04      28.000000
50%       130.00000    1.303575e+05  1.351375e+05      56.000000
75%       203.00000    2.030942e+05  2.027012e+05      85.000000
max       272.00000    2.373711e+06  2.415841e+06     114.000000

            PROD_QTY      TOT_SALES
count  264836.000000  264836.000000
mean        1.907309       7.304200
std         0.643654       3.083226
min         1.000000       1.500000
25%         2.000000       5.400000
50%         2.000000       7.400000
75%         2.000000       9.200000
max       200.000000     650.000000
```

```
# Calculate the Z-scores for the TOT_SALES column
sales_behavior_df['Z_SCORE'] = (sales_behavior_df['TOT_SALES'] -
sales_behavior_df['TOT_SALES'].mean()) /
sales_behavior_df['TOT_SALES'].std()

# Define a threshold for identifying outliers
threshold = 3

# Identify outliers
outliers = sales_behavior_df[sales_behavior_df['Z_SCORE'].abs() >
threshold]
```

```
# Print the outliers
outliers.count()
```

```
DATE                439
STORE_NBR           439
LYLTY_CARD_NBR      439
TXN_ID              439
PROD_NBR            439
PROD_NAME           439
PROD_QTY            439
TOT_SALES           439
LIFESTAGE           439
PREMIUM_CUSTOMER    439
Z_SCORE             439
dtype: int64
```

```
sales_behavior_df.head()
```

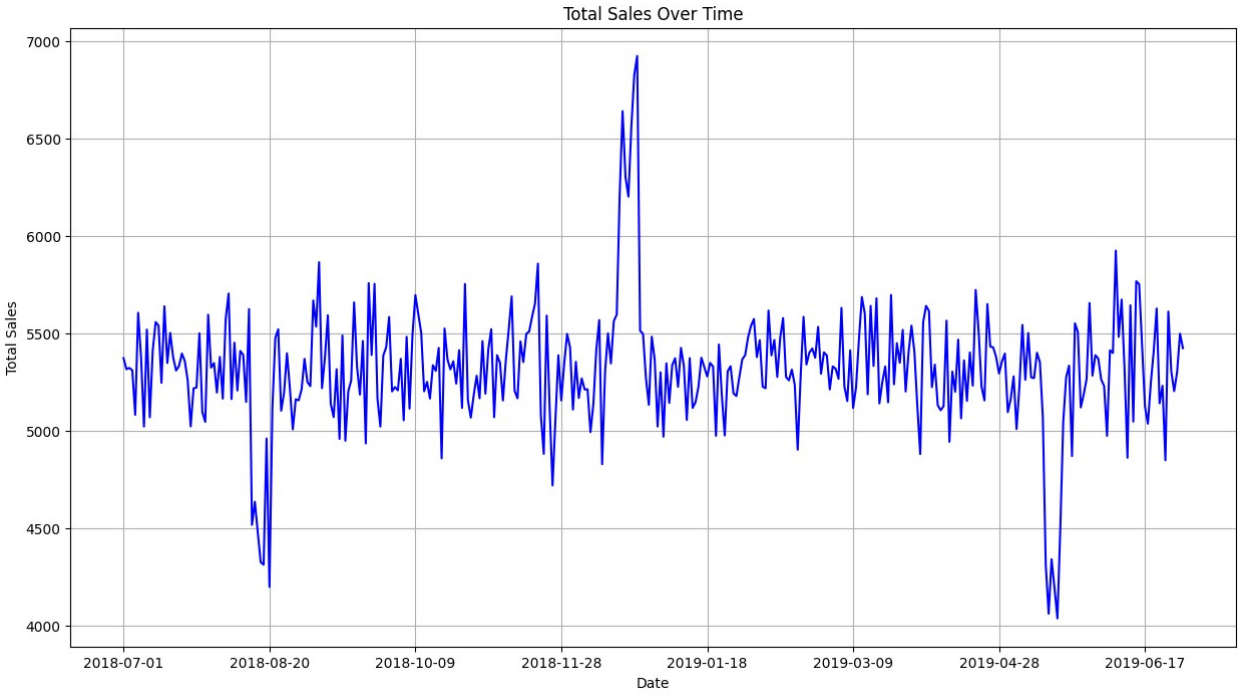
```
         DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
0  2018-10-17          1            1000       1         5
1  2019-05-14          1            1307     348        66
2  2019-05-20          1            1343     383        61
3  2018-08-17          2            2373     974        69
4  2018-08-18          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

                LIFESTAGE PREMIUM_CUSTOMER
0   YOUNG SINGLES/COUPLES          Premium
1  MIDAGE SINGLES/COUPLES           Budget
2  MIDAGE SINGLES/COUPLES           Budget
3  MIDAGE SINGLES/COUPLES           Budget
4  MIDAGE SINGLES/COUPLES           Budget
```

Start the analysis

First we need to plot the data to see if there're any visually visible outliers

```
# Group by DATE and sum the TOT_SALES
sales_by_date = sales_behavior_df.groupby('DATE')['TOT_SALES'].sum()

# Plot the line chart
plt.figure(figsize=(15, 8))
sales_by_date.plot(kind='line', color='blue')
plt.xlabel('Date')
plt.ylabel('Total Sales')
```

```
plt.title('Total Sales Over Time')
plt.grid(True)
plt.show()
```



We see here that there're outliers in the data, so we start by isolating them to find out their size in proportion to the actual data

```
outliers = sales_by_date[(sales_by_date > 5700) | (sales_by_date <
4700)]

filtered_sales_count = outliers.count()
total_sales_count = sales_behavior_df["TOT_SALES"].count()
percentage_of_outliers = ((filtered_sales_count / total_sales_count))
* 100
print("Percentage of outliers in the total sales: ",
percentage_of_outliers)
```

```
Percentage of outliers in the total sales:  0.010950172937213974
```

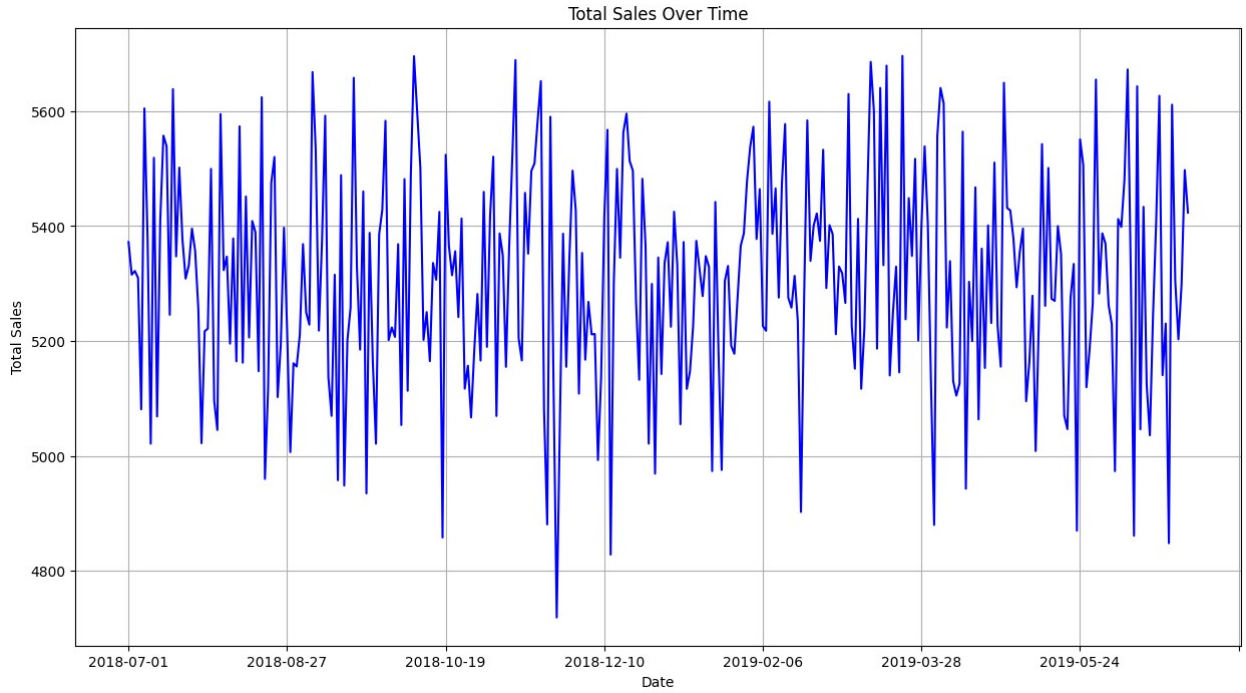
Here we see that the percentage is very low, so we drop the outliers

```
# Iterate through the outliers and drop them from the
sales_behavior_df
# Iterate through the outliers and drop them from the
sales_behavior_df
sales_behavior_df =
sales_behavior_df[~sales_behavior_df['DATE'].isin(outliers.index)]
```

```
# Save the modified dataframe to the original file
sales_behavior_df.to_csv("sales_behavior.csv")
```

Then we run the same graph one more time to see the difference

```
# Group by DATE and sum the TOT_SALES
sales_by_date = sales_behavior_df.groupby('DATE')['TOT_SALES'].sum()

# Plot the line chart
plt.figure(figsize=(15, 8))
sales_by_date.plot(kind='line', color='blue')
plt.xlabel('Date')
plt.ylabel('Total Sales')
plt.title('Total Sales Over Time')
plt.grid(True)
plt.show()
```



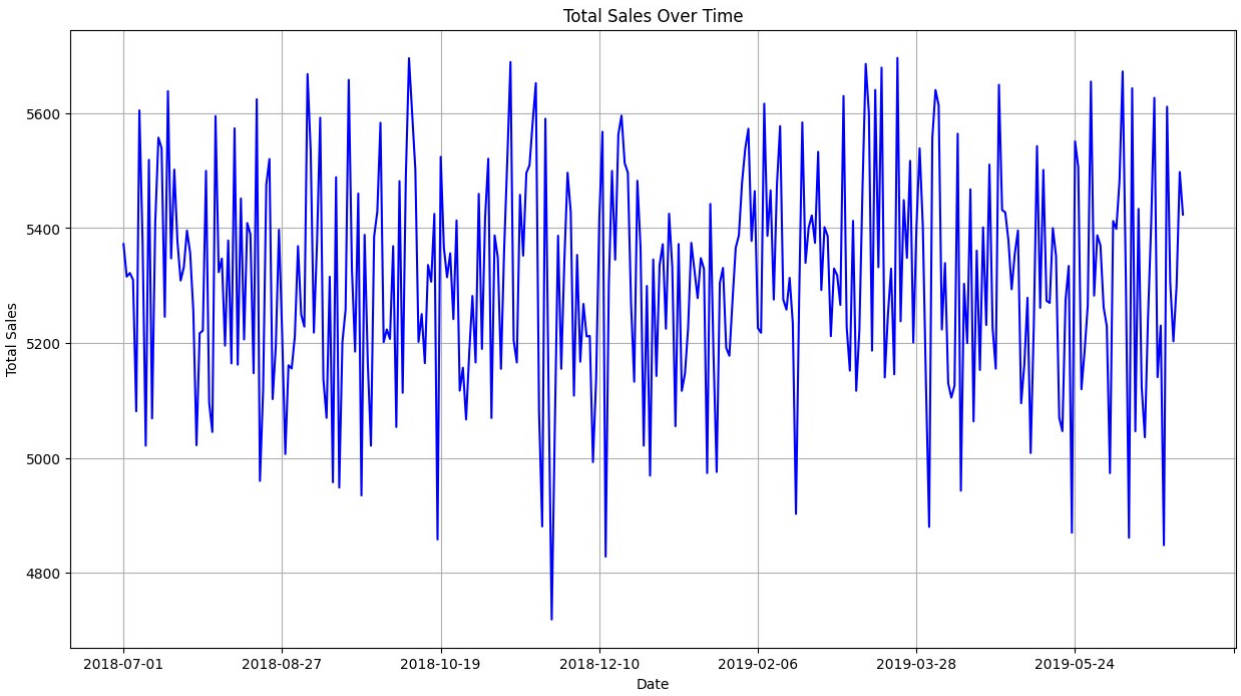
Now that we removed all outliers, we continue with the analysis.

```
relationship = pd.crosstab(sales_behavior_df['LIFESTAGE'],
sales_behavior_df['PREMIUM_CUSTOMER'])
print(relationship)
```

```
PREMIUM_CUSTOMER        Budget  Mainstream  Premium
LIFESTAGE
MIDAGE SINGLES/COUPLES    4591       10883     7484
NEW FAMILIES              2761        2127     1457
OLDER FAMILIES           21199       13020    10302
OLDER SINGLES/COUPLES    16806       16638    16189
```

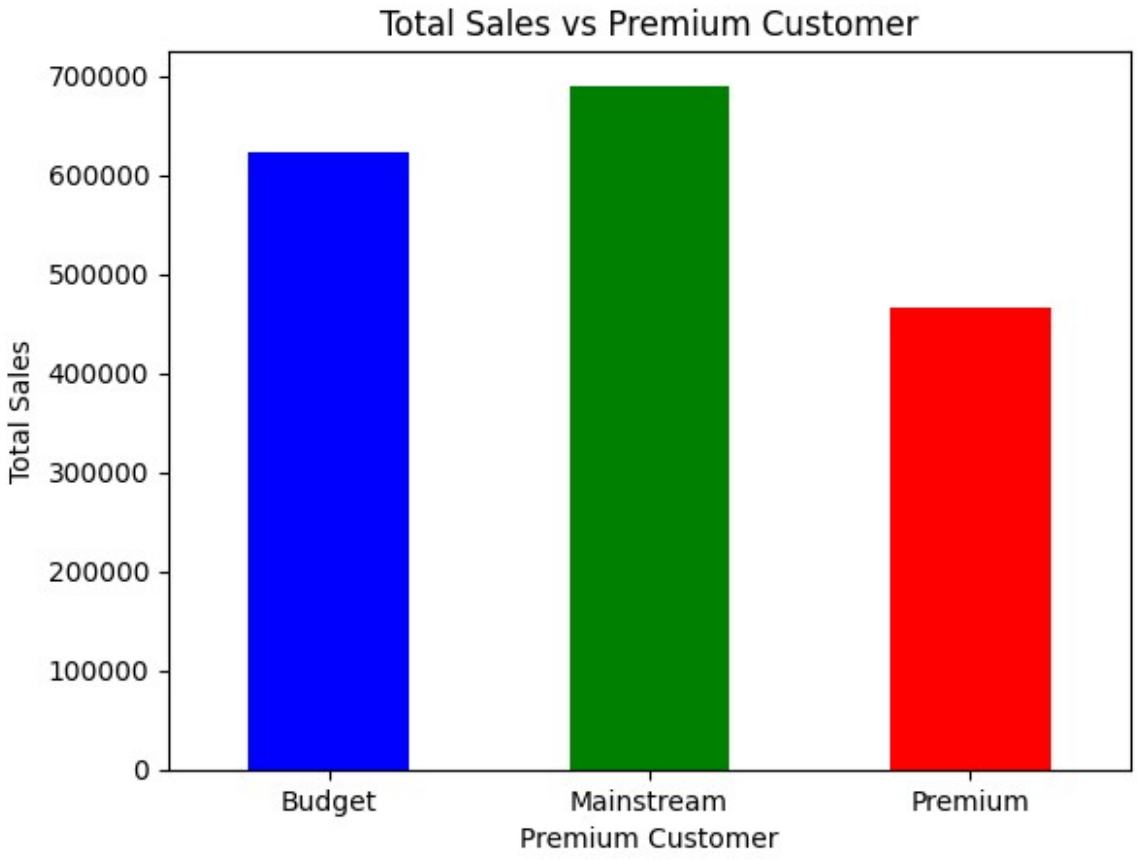
```
RETIREES                  13891       19547    11959
YOUNG FAMILIES            17522       11847    10555
YOUNG SINGLES/COUPLES      8451       19099     5737
```

```
import matplotlib.pyplot as plt

# Plot the line chart for total sales over time
plt.figure(figsize=(15, 8))
sales_by_date.plot(kind='line', color='blue')
plt.xlabel('Date')
plt.ylabel('Total Sales')
plt.title('Total Sales Over Time')
plt.grid(True)
plt.show()
```




```
import matplotlib.pyplot as plt

# Group by PREMIUM_CUSTOMER and sum the TOT_SALES
sales_by_customer = sales_behavior_df.groupby('PREMIUM_CUSTOMER')
['TOT_SALES'].sum()

# Plot the bar chart with colors and save the plot as an image
colors = ['blue', 'green', 'red']
sales_by_customer.plot(kind='bar', color=colors, rot=0)
plt.xlabel('Premium Customer')
plt.ylabel('Total Sales')
plt.title('Total Sales vs Premium Customer')
```

```
plt.savefig('total_sales_vs_premium_customer.png')
plt.show()
```



From the previous two figures we see that the highest total sales is coming from

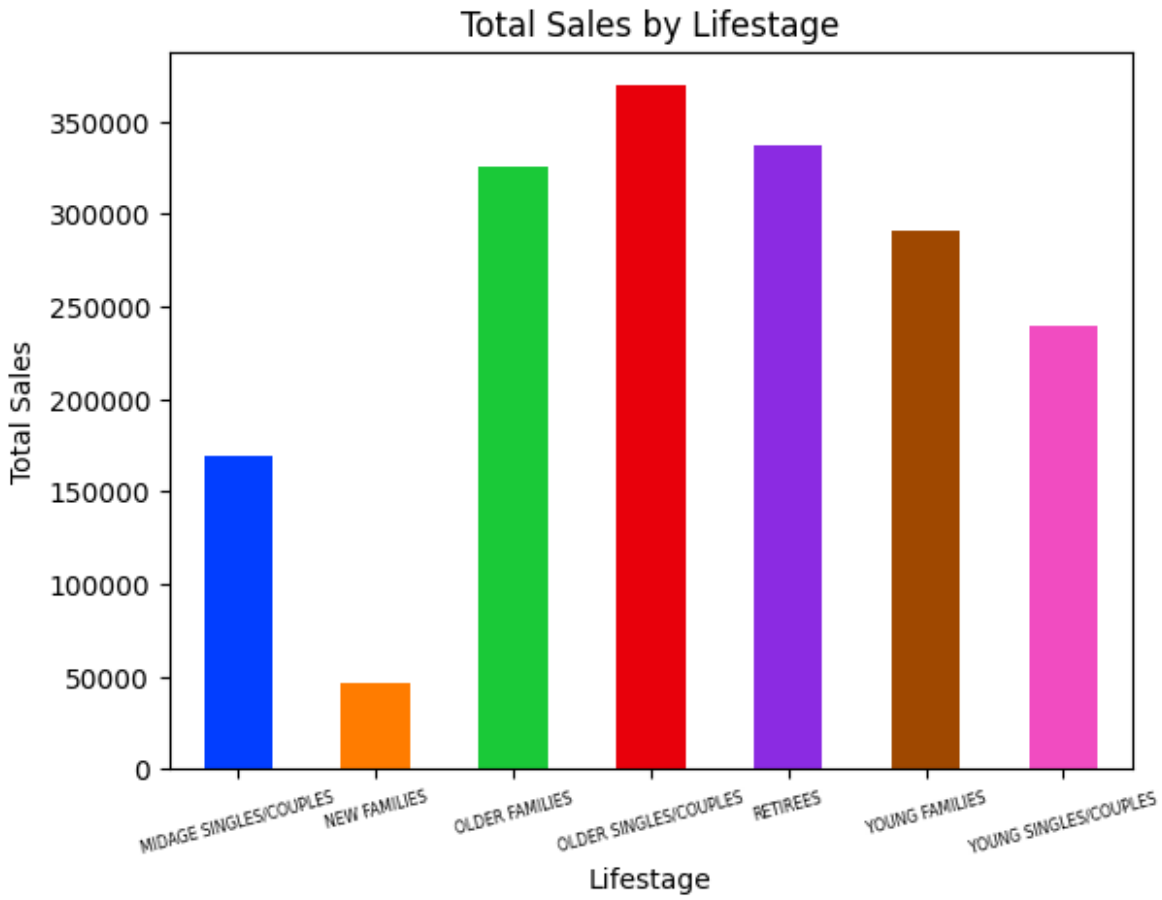
1- the Mainstream and the streams descending are RETIREES, YOUNG SINGLES/COUPLES, OLDER SINGLES/COUPLES 2- Then the Budget with the streams OLDER FAMILIES, YOUNG FAMILIES, OLDER SINGLES/COUPLES 3- Then the Premium with the streams OLDER SINGLES/COUPLES, RETIREES, YOUNG FAMILIES

```
sales_behavior_df["TOT_SALES"].sum()
```

```
np.float64(1778995.5999999999)
```

```
import seaborn as sns
import matplotlib.pyplot as plt

# Group by LIFESTAGE and sum the TOT_SALES
sales_by_lifestage = sales_behavior_df.groupby('LIFESTAGE')
['TOT_SALES'].sum()
```

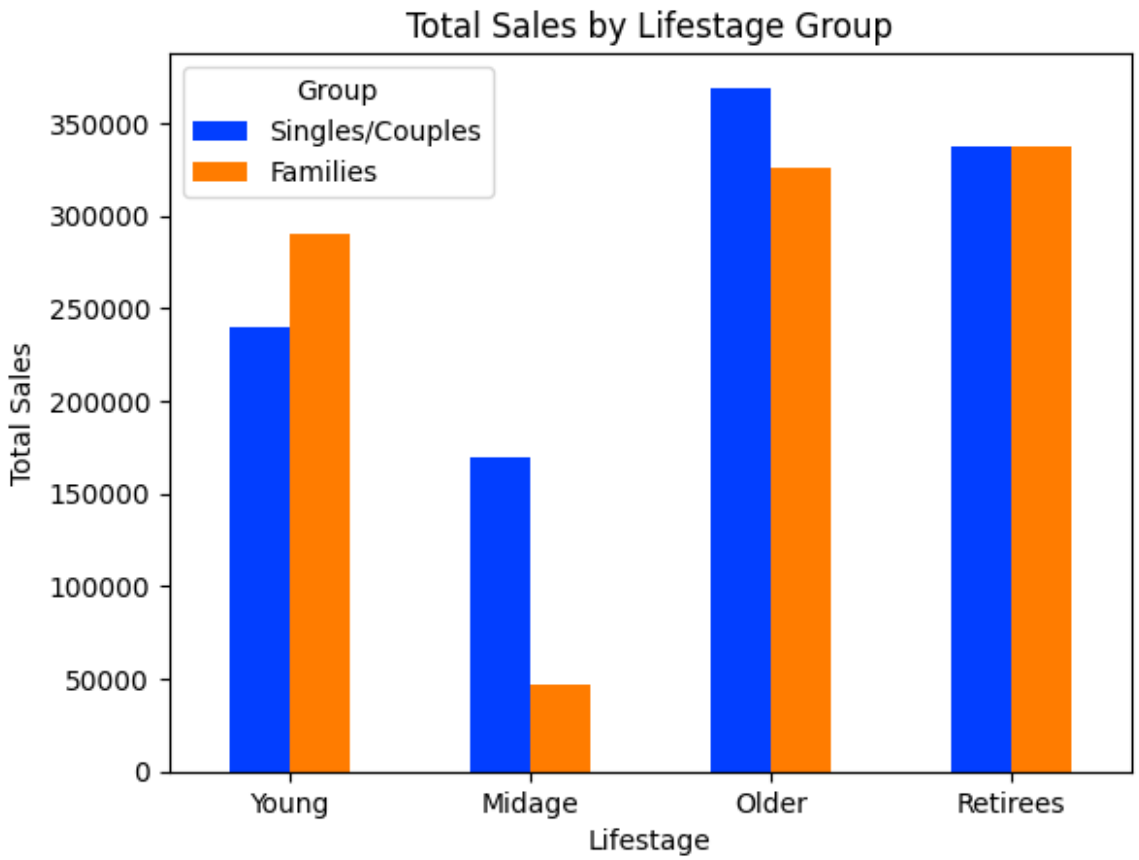
```
# Get a bright color palette with the same number of colors as the
number of unique LIFESTAGE categories
unique_lifestages = sales_behavior_df['LIFESTAGE'].unique()
colors = sns.color_palette('bright', len(unique_lifestages))

# Plot the bar chart with distinct bright colors for each LIFESTAGE
sales_by_lifestage.plot(kind='bar', color=colors, rot=45)
plt.xlabel('Lifestage')
plt.ylabel('Total Sales')
plt.title('Total Sales by Lifestage')
plt.xticks(rotation=15, fontsize=5.5)
plt.show()
```




```
# Group by LIFESTAGE and sum the TOT_SALES
sales_by_lifestage = sales_behavior_df.groupby('LIFESTAGE')
['TOT_SALES'].sum()
sales_by_lifestage = sales_by_lifestage.sort_values(ascending=False)
print(sales_by_lifestage)

LIFESTAGE
OLDER SINGLES/COUPLES     402426.75
```

```
RETIREES                  366470.90
OLDER FAMILIES            353767.20
YOUNG FAMILIES            316160.10
YOUNG SINGLES/COUPLES     260405.30
MIDAGE SINGLES/COUPLES    184751.30
NEW FAMILIES               50433.45
Name: TOT_SALES, dtype: float64
```

```
# Combine family groups with the corresponding singles/couples
combined_sales = sales_behavior_df.groupby('LIFESTAGE')
['TOT_SALES'].sum()
combined_sales = combined_sales.reindex(['YOUNG SINGLES/COUPLES',
'YOUNG FAMILIES',
                                         'MIDAGE SINGLES/COUPLES',
'NEW FAMILIES',
                                         'OLDER SINGLES/COUPLES',
'OLDER FAMILIES',
                                         'RETIREES'])

# Create a new DataFrame for plotting
plot_data = pd.DataFrame({
    'Singles/Couples': combined_sales[['YOUNG SINGLES/COUPLES',
'MIDAGE SINGLES/COUPLES', 'OLDER SINGLES/COUPLES',
'RETIREES']].values,
    'Families': combined_sales[['YOUNG FAMILIES', 'NEW FAMILIES',
'OLDER FAMILIES', 'RETIREES']].values
}, index=['Young', 'Midage', 'Older', 'Retirees'])

# Plot the clustered column chart
plot_data.plot(kind='bar', color=colors[:2], rot=0)
plt.xlabel('Lifestage')
plt.ylabel('Total Sales')
plt.title('Total Sales by Lifestage Group')
plt.xticks(rotation=0)
plt.legend(title='Group')
plt.show()
```

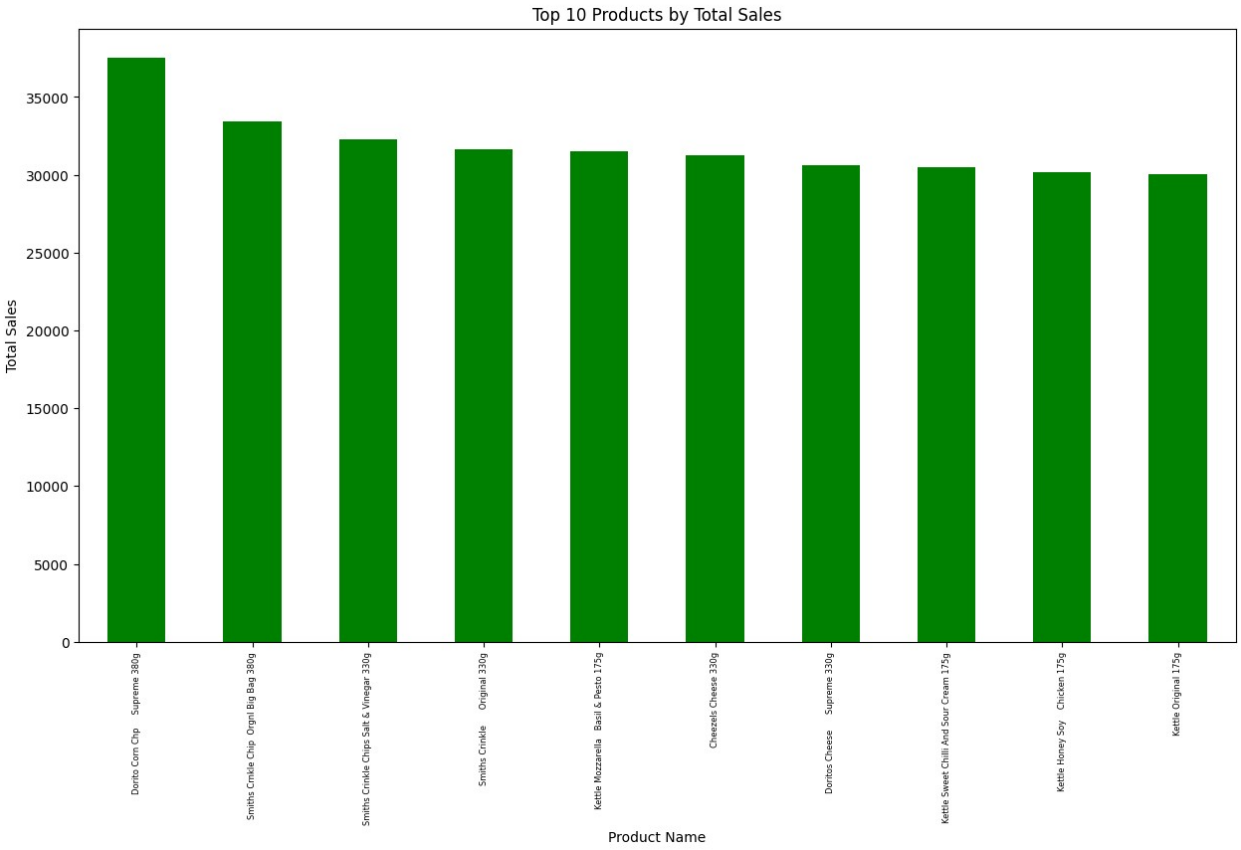


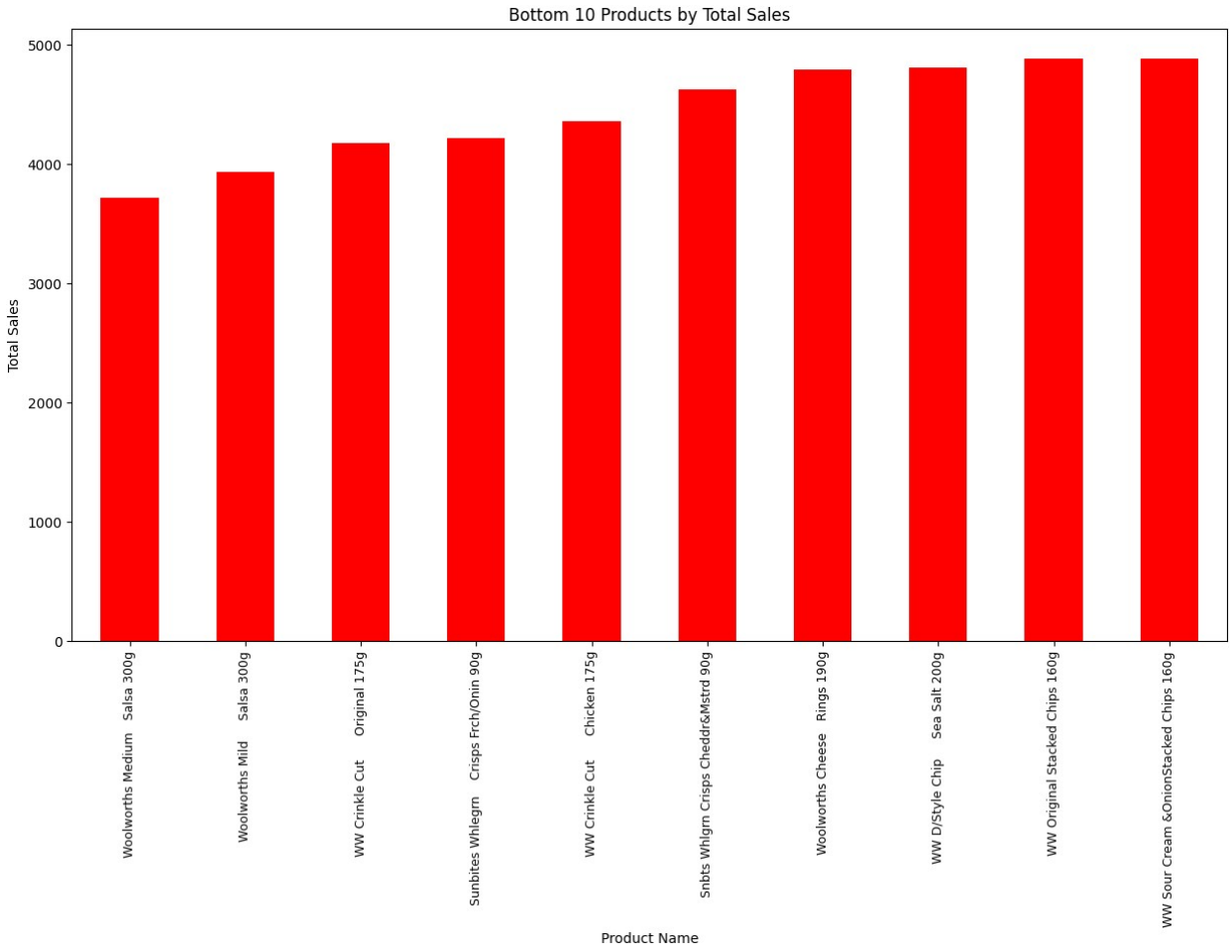

```
num_products = sales_behavior_df['PROD_NAME'].nunique()
print("Number of different products:", num_products)
```

```
Number of different products: 114
```

```
import matplotlib.pyplot as plt

# Group by PROD_NAME and sum the TOT_SALES
sales_by_product = sales_behavior_df.groupby('PROD_NAME')
['TOT_SALES'].sum()

# Sort the sales by product in descending order and select the top 10
and bottom 10
top_10_sales_by_product =
sales_by_product.sort_values(ascending=False).head(10)
bottom_10_sales_by_product =
sales_by_product.sort_values(ascending=True).head(10)

# Plot the bar chart for top 10 products
plt.figure(figsize=(15, 8))
top_10_sales_by_product.plot(kind='bar', color='green')
plt.xlabel('Product Name')
plt.ylabel('Total Sales')
```

```
plt.title('Top 10 Products by Total Sales')
plt.xticks(rotation=90, fontsize=6)
plt.show()

# Plot the bar chart for bottom 10 products
plt.figure(figsize=(15, 8))
bottom_10_sales_by_product.plot(kind='bar', color='red')
plt.xlabel('Product Name')
plt.ylabel('Total Sales')
plt.title('Bottom 10 Products by Total Sales')
plt.xticks(rotation=90, fontsize=9)
plt.show()
```

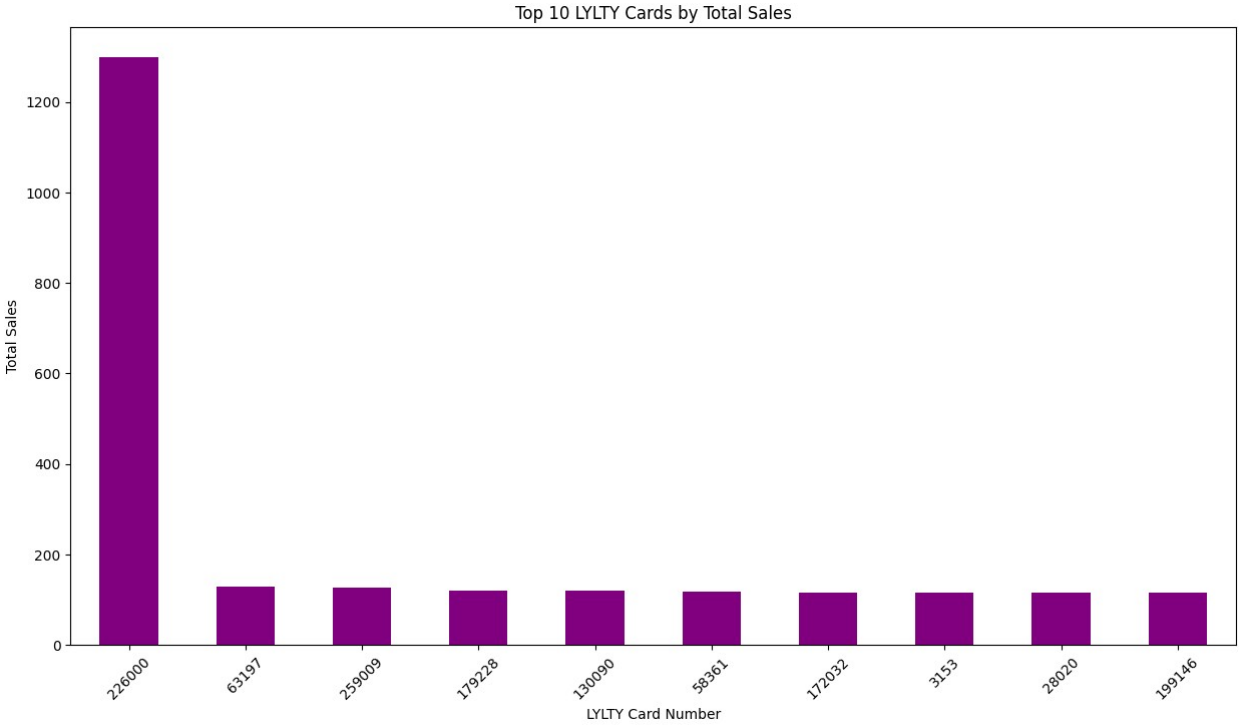





```
lylty_card_count = sales_behavior_df.groupby('LYLTY_CARD_NBR').size()
print("Number of different LYLTY_CARD_NBR:", lylty_card_count.count())
```

```
Number of different LYLTY_CARD_NBR: 70942
```

```
# Group by LYLTY_CARD_NBR and sum the TOT_SALES
sales_by_card = sales_behavior_df.groupby('LYLTY_CARD_NBR')
['TOT_SALES'].sum()

# Sort the sales by card in descending order and select the top 10
top_10_sales_by_card =
sales_by_card.sort_values(ascending=False).head(10)

# Plot the bar chart for top 10 LYLTY cards
plt.figure(figsize=(15, 8))
top_10_sales_by_card.plot(kind='bar', color='purple')
plt.xlabel('LYLTY Card Number')
plt.ylabel('Total Sales')
plt.title('Top 10 LYLTY Cards by Total Sales')
plt.xticks(rotation=45)
plt.show()
```



We can see here that there's one loyalty card that is driving a very large amount of sales that's worth looking into.