#### In [1]:

```
import pandas as pd
import numpy as np
from IPython.display import Image # To display images in jupyter notebook
from matplotlib import pyplot as plt
import seaborn as sns
plt.style.use("ggplot")
```

#### In [2]:

```
transaction_df = pd.read_excel(io='transaction_data.xlsx')
customer_df = pd.read_excel(io='purchase_behaviour.xlsx')
```

## **Analyse Transaction Data**

#### In [3]:

```
print(transaction_df.shape)
transaction_df.head()
```

(264836, 8)

#### Out[3]:

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

#### In [4]:

```
# Check for any null value in 'DATE'
any(transaction_df['DATE'].isna())
```

#### Out[4]:

False

#### In [5]:

```
# Bring date to their propper format

from datetime import date, timedelta

start_date = date(1899, 12, 30) # excel start date

new_dates = [start_date + timedelta(days=days) for days in transaction_df['DATE']]

transaction_df['DATE'] = new_dates
```

#### In [6]:

transaction\_df.head()

#### Out[6]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	T
0	2018- 10-17	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	_
1	2019- 05-14	1	1307	348	66	CCs Nacho Cheese 175g	3	
2	2019- 05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	
3	2018- 08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	
4	2018- 08-18	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	
4							<b></b>	•

#### In [7]:

```
# Seperate Weight from the product name
```

PROD\_WEIGHT = [product[len(product)-4: len(product)-1] for product in transaction\_df['PROD\_transaction\_df['PROD\_WEIGHT(g)'] = PROD\_WEIGHT

#### In [8]:

```
transaction_df.head()
```

#### Out[8]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	T
0	2018- 10-17	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	_
1	2019- 05-14	1	1307	348	66	CCs Nacho Cheese 175g	3	
2	2019- 05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	
3	2018- 08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	
4	2018- 08-18	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	
4							•	,

#### In [9]:

```
transaction_df['PROD_WEIGHT(g)'].unique()
```

#### Out[9]:

```
array(['175', '170', '150', '300', '330', '210', '270', '220', '125', '110', '134', '380', '180', '165', 'Sal', '250', '200', '160', '190', '90', '70'], dtype=object)
```

Here we have 'Sal' in unique value... Now we will deal with it.

#### In [10]:

```
# Check which Product gives us 'Sal' in PROD_WEIGHT(g)

f_mask = (transaction_df['PROD_WEIGHT(g)'] == 'Sal')

t_d = transaction_df[f_mask]

t_d.head()
```

#### Out[10]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY ·
65	2019- 05-20	83	83008	82099	63	Kettle 135g Swt Pot Sea Salt	2
153	2019- 05-17	208	208139	206906	63	Kettle 135g Swt Pot Sea Salt	1
174	2018- 08-20	237	237227	241132	63	Kettle 135g Swt Pot Sea Salt	2
177	2019- 05-17	243	243070	246706	63	Kettle 135g Swt Pot Sea Salt	1
348	2018- 10-26	7	7077	6604	63	Kettle 135g Swt Pot Sea Salt	2
4							•

#### In [11]:

```
t_d['PROD_NAME'] .unique()
```

#### Out[11]:

array(['Kettle 135g Swt Pot Sea Salt'], dtype=object)

## We see that name is 'Kettle 135g Swt Pot Sea' is not fomatted like other Product names.

#### In [12]:

```
# <<--- Replace all 'Kettle 135g Swt Pot Sea' with 'Kettle Swt Pot Sea' from PROD_NAME colu
transaction_df['PROD_NAME'].replace(to_replace='Kettle 135g Swt Pot Sea', value='Kettle Swt
# <<--- Replace all 'Sal' with 135 from PROD_WEIGHT(g) column --->>
transaction_df['PROD_WEIGHT(g)'].replace(to_replace='Sal', value=135, inplace=True)
```

#### In [13]:

```
# Seperate Name from the product name

PROD_NAME = [product[: len(product)-4].strip() for product in transaction_df['PROD_NAME']]
transaction_df['PROD_NAME'] = PROD_NAME
```

#### In [14]:

```
# Merge both the data frames

df = pd.merge(left=transaction_df, right=customer_df, on='LYLTY_CARD_NBR')
df.head()
```

#### Out[14]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	то
0	2018- 10-17	1	1000	1	5	Natural Chip Compny SeaSalt	2	
1	2019- 05-14	1	1307	348	66	CCs Nacho Cheese	3	
2	2018- 11-10	1	1307	346	96	WW Original Stacked Chips	2	
3	2019- 03-09	1	1307	347	54	CCs Original	1	
4	2019- 05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken	2	
4								•

#### In [15]:

```
# Convert PROD_WEIGHT(g) from string datatype to interger

df['PROD_WEIGHT(g)'] = df['PROD_WEIGHT(g)'].astype(int)
```

#### In [16]:

```
# Convert DATE from object to datetime

df['DATE'] = pd.to_datetime(df['DATE'], format='%Y-%m-%d')
```

#### In [17]:

```
df.info()
```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 264836 entries, 0 to 264835

Data columns (total 11 columns):

DATE 264836 non-null datetime64[ns]

STORE\_NBR 264836 non-null int64 264836 non-null int64 LYLTY\_CARD\_NBR  $TXN_ID$ 264836 non-null int64 264836 non-null int64 PROD NBR PROD\_NAME 264836 non-null object 264836 non-null int64 PROD\_QTY TOT\_SALES 264836 non-null float64 PROD\_WEIGHT(g) 264836 non-null int32 264836 non-null object LIFESTAGE PREMIUM CUSTOMER 264836 non-null object

dtypes: datetime64[ns](1), float64(1), int32(1), int64(5), object(3)

memory usage: 23.2+ MB

#### There is no Null value in any column/feature

#### In [18]:

df.describe()

#### Out[18]:

	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_QTY	TOT_S/
count	264836.00000	2.648360e+05	2.648360e+05	264836.000000	264836.000000	264836.00
mean	135.08011	1.355495e+05	1.351583e+05	56.583157	1.907309	7.30
std	76.78418	8.057998e+04	7.813303e+04	32.826638	0.643654	3.08
min	1.00000	1.000000e+03	1.000000e+00	1.000000	1.000000	1.50
25%	70.00000	7.002100e+04	6.760150e+04	28.000000	2.000000	5.40
50%	130.00000	1.303575e+05	1.351375e+05	56.000000	2.000000	7.40
75%	203.00000	2.030942e+05	2.027012e+05	85.000000	2.000000	9.20
max	272.00000	2.373711e+06	2.415841e+06	114.000000	200.000000	650.00
4						<b>•</b>

From above metric we see that TOT\_SALES have standard deviation more than 3, and acceptable scale is from -3 to 3 so there might be outliars.

#### In [19]:

```
# Checking for outliars in TOT_SALES by histogram and Boxplot

fig1, ax1 =plt.subplots(nrows=1, ncols=2, figsize=(15, 4))

total_sales = df['TOT_SALES']

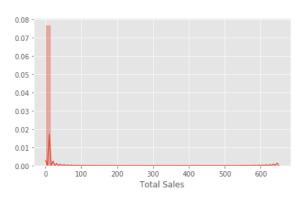
sns.distplot(a=total_sales, kde=True, ax=ax1[0], axlabel='Total Sales') # Histogram
print(f"Skewness of Total Sales: {df['TOT_SALES'].skew()}")

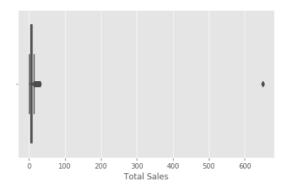
sns.boxplot(x=total_sales, color='orange', ax=ax1[1]) # Boxplot
ax1[1].set(xlabel="Total Sales")
```

Skewness of Total Sales: 68.56963132181272

#### Out[19]:

[Text(0.5, 0, 'Total Sales')]





#### There are outliars above 600.

#### In [20]:

```
df[df['TOT_SALES'] > 600]
```

#### Out[20]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY
71456	2018- 08-19	226	226000	226201	4	Dorito Corn Chp Supreme	200
71457	2019- 05-20	226	226000	226210	4	Dorito Corn Chp Supreme	200
4							•

#### As you see there are tow extremely large outliars, These both outliars are by

the same person having LYLTY\_CARD\_NBR as 226000. This person buy 200 packets of 'Dorito Corn Chp Supreme' of weight 380g each both the times. Most importantly these 2 transactions are not frequent, as he/she buys these 200 packets 2 times in timespan of 2 years. So these can be regarded as outliars. Therefore we will remove these 2 transactions.

```
In [21]:
```

```
df = df[df['TOT_SALES'] < 600] # Remove the outliars</pre>
```

#### In [22]:

```
# Recheck outliars

fig1, ax1 =plt.subplots(nrows=1, ncols=2, figsize=(15, 4))

total_sales = df['TOT_SALES']

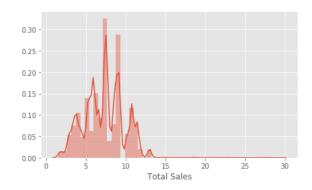
sns.distplot(a=total_sales, kde=True, ax=ax1[0], axlabel='Total Sales') # Histogram
print(f"Skewness of Total Sales: {df['TOT_SALES'].skew()}")

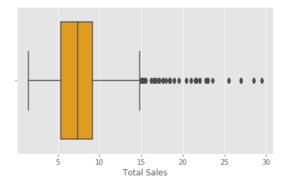
sns.boxplot(x=total_sales, color='orange', ax=ax1[1]) # Boxplot
ax1[1].set(xlabel="Total Sales")
```

Skewness of Total Sales: 0.3131546350495999

#### Out[22]:

[Text(0.5, 0, 'Total Sales')]





#### You see still we got outliars, Lets figure out these outliars.

#### In [23]:

```
# Check the occurances of product quantity's in these outliars.
outliars = df[df['TOT_SALES'] > 15]
outliars['PROD_QTY'].value_counts()
```

#### Out[23]:

```
5 2884 1813 69
```

Name: PROD\_QTY, dtype: int64

#### In [24]:

```
outliars['LIFESTAGE'].value_counts()
```

#### Out[24]:

OLDER SINGLES/COUPLES 119
OLDER FAMILIES 114
YOUNG FAMILIES 99
RETIREES 91
MIDAGE SINGLES/COUPLES 53
YOUNG SINGLES/COUPLES 53
NEW FAMILIES 9
Name: LIFESTAGE, dtype: int64

You see quantities we get are in range 3 to 5, and we see that maximum people in this group are who are Old/Retirees or Old/Young families. Therefore it is not a surprise that a Family person buys 3 or 4 packet of chips. So these outliars can be accepted.

#### In [25]:

```
# Save Merged DataFrame

df.to_excel(excel_writer='Merged_data_frame.xlsx', sheet_name='Sheet1')
```

#### In [26]:

```
df.head()
```

#### Out[26]:

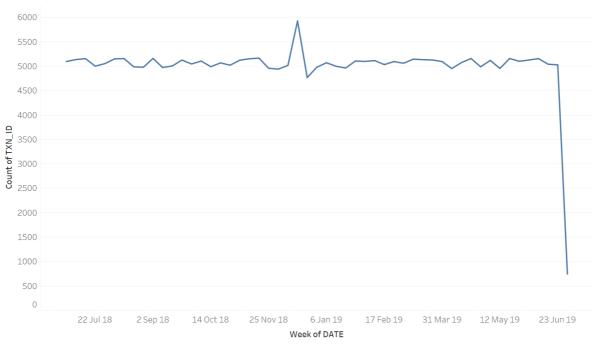
	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	то
0	2018- 10-17	1	1000	1	5	Natural Chip Compny SeaSalt	2	
1	2019- 05-14	1	1307	348	66	CCs Nacho Cheese	3	
2	2018- 11-10	1	1307	346	96	WW Original Stacked Chips	2	
3	2019- 03-09	1	1307	347	54	CCs Original	1	
4	2019- 05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken	2	
4								•

#### In [27]:

```
# Transactions over time (Week)
Image('image1.png')
```

#### Out[27]:

#### Transactions over Time



The trend of count of TXN\_ID for DATE Week.

Here we assume that year starts from July 2018 and ends at June 2019, rather than Jan 2018 to Dec 2019 (atleast in India).

Here we see that Transactions are almost same all over the year, but there is 1 high Spike.

```
In [28]:
```

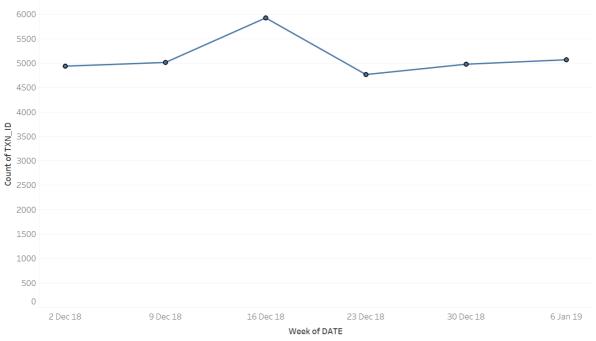
```
# <<<--- High Spike --->>
```

#### In [29]:

Image('image2.png')

#### Out[29]:

#### Transactions over Time (Highest Spike)



The trend of count of TXN\_ID for DATE Week. The data is filtered on DATE Week, which keeps 6 of 53 members

#### In [30]:

```
# Here we analyse customer from '9 Dec 2018' to '23 Dec 2018'
from datetime import datetime
filter_mask = (df['DATE'] >= '2018-12-9') & (df['DATE'] <= '2018-12-30')
temp_df1 = df[filter_mask]
temp_df1.head()</pre>
```

#### Out[30]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY TO
10	2018- 12-12	4	4074	2980	4	Dorito Corn Chp Supreme	2
41	2018- 12-28	9	9208	8633	24	Grain Waves Sweet Chilli	2
43	2018- 12-18	13	13213	12448	53	RRD Sweet Chilli & Sour Cream	2
50	2018- 12-26	19	19272	16684	59	Old El Paso Salsa Dip Tomato Med	1
64	2018- 12-20	23	23067	19159	68	Pringles Chicken Salt Crips	2
4							<b>•</b>

You see that great spike in the graph is between '9 dec 2018' to '24 dec 2018', So now we will analyse all date between '15 dec 2018' to '30 dec 2018'.

#### In [31]:

```
# Count of transctions from 2018-12-09 to 2018-12-30
temp_df1.groupby(by='DATE').count()['TXN_ID']
```

#### Out[31]:

```
DATE
2018-12-09
               697
2018-12-10
              715
2018-12-11
              750
2018-12-12
               664
2018-12-13
              720
2018-12-14
              744
2018-12-15
              725
2018-12-16
               761
2018-12-17
               786
2018-12-18
              862
2018-12-19
              906
2018-12-20
               855
2018-12-21
               842
2018-12-22
               915
2018-12-23
               917
2018-12-24
              939
2018-12-26
              753
2018-12-27
              732
2018-12-28
               720
2018-12-29
               706
2018-12-30
               747
Name: TXN_ID, dtype: int64
```

#### Results:-

- 1. There is no transactions for date 25 dec 2018 (maybe shop's will be closed on Christmas).
- 2. The transactions keep on increasing (ie.more than average ie. from 700's to 900's) till date 24 dec 2018 (ie. a day before Christmas) and then after Christmas (ie. 25 dec 2018), the transactions comes to average (ie. 700's).

#### Conclusion:-

Highest Chips are sold near Christmas.

In [32]:

df.head()

Out[32]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	то
0	2018- 10-17	1	1000	1	5	Natural Chip Compny SeaSalt	2	
1	2019- 05-14	1	1307	348	66	CCs Nacho Cheese	3	
2	2018- 11-10	1	1307	346	96	WW Original Stacked Chips	2	
3	2019- 03-09	1	1307	347	54	CCs Original	1	
4	2019- 05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken	2	
4								•

## Lets Check weather pack size matters or not.

In [33]:

# <<--- Number of transactions per weight --->>

#### In [34]:

df.head()

#### Out[34]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	то
0	2018- 10-17	1	1000	1	5	Natural Chip Compny SeaSalt	2	
1	2019- 05-14	1	1307	348	66	CCs Nacho Cheese	3	
2	2018- 11-10	1	1307	346	96	WW Original Stacked Chips	2	
3	2019- 03-09	1	1307	347	54	CCs Original	1	
4	2019- 05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken	2	
4								•

#### In [35]:

```
temp3 = df['PROD_WEIGHT(g)'].value_counts(normalize=True)
x = temp3.index
y = temp3

data = list(zip(x, y))
t_df = pd.DataFrame(data=data, index=range(0, len(x)), columns=['Product_Weight', 'Count_Pet_df['Count_Percentage_TXN_ID(%)'] = [round(per * 100, 1) for per in t_df['Count_Percentaget_df.sort_values('Count_Percentage_TXN_ID(%)', ascending=False, inplace=True)
t_df['Product_Weight'] = [str(weight) for weight in t_df['Product_Weight']]

t_df.to_excel(excel_writer='ProductWeight_TransactionCount.xlsx', sheet_name='Sheet1')
```

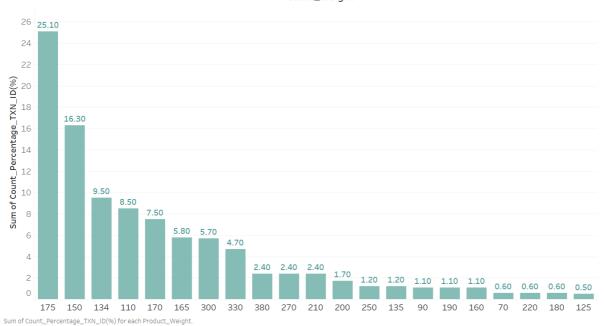
#### In [36]:

```
# <<--- Number of Transaction per Product Weight --->>
Image('image3.png')
```

#### Out[36]:

#### Transaction Count per Product weight.

#### Product\_Weight



Conclusion :- Most packets that are sold are of average weight 175g, 150g, 134g, 110g, 170g.

## **Analysis on Customer Segment**

#### In [37]:

df.head()

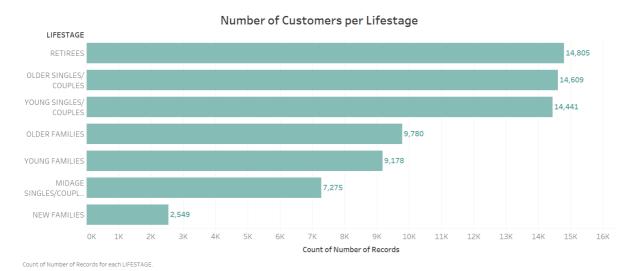
#### Out[37]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	то
0	2018- 10-17	1	1000	1	5	Natural Chip Compny SeaSalt	2	
1	2019- 05-14	1	1307	348	66	CCs Nacho Cheese	3	
2	2018- 11-10	1	1307	346	96	WW Original Stacked Chips	2	
3	2019- 03-09	1	1307	347	54	CCs Original	1	
4	2019- 05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken	2	
4								•

#### In [38]:

# <<<--- Type of Customer's (acc. to LIFESTAGE) that are more interested in buying Chips -Image('image4.png')</pre>

#### Out[38]:



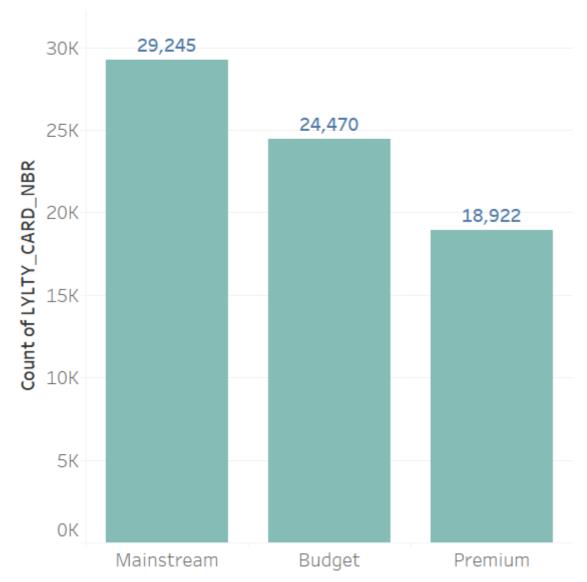
## Conclusion :- Customers who mostly buy chips Retirees and single/couples.

```
In [39]:
```

```
# <<<--- Type of Customer's (acc. to Category) that are more interested in buying Chips ---
Image('image5.png')</pre>
```

Out[39]:

## Number of Customers per Category



Count of LYLTY\_CARD\_NBR for each PREMIUM\_CUSTOMER.

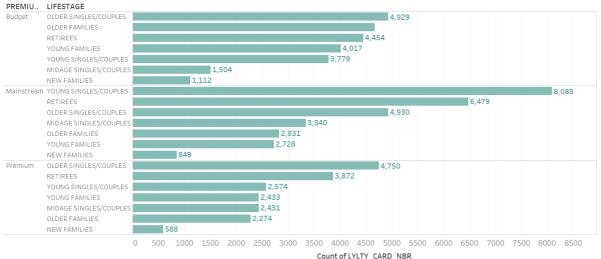
Conlcusion :- People with category mainstream more likely to buy chips followed by the budget category and premium customers less likely to buy chips!

#### In [40]:

```
# <<<---- Customer counts on basis category and subcategory ---->>>
Image('image6.png')
```

#### Out[40]:





Count of LYLTY CARD NBR for each LIFESTAGE broken down by PREMIUM CUSTOMER.

#### Results:-

#### Here we have 3 main categories :-

- 1. Budget
- 2. Mainstream
- 3. Premium

### All three categories have further 7 further categories :-

- 1. OLDER FAMILIES
- 2. YOUNG FAMILIES
- 3. NEW FAMILIES
- 4. OLDER SINGLE/COUPLES
- 5. YOUNG SINGLE/COUPLES
- 6. MIDAGE SINGLE/COUPLES
- 7. RETIREES

#### Result1 (Budget) :-

In Budget category everyone love to buy chips except mainstream single/couples.

#### Result2 (Mainstream) :-

In Mainstream Young/Single couples and families and retirees more likely to buy chips.

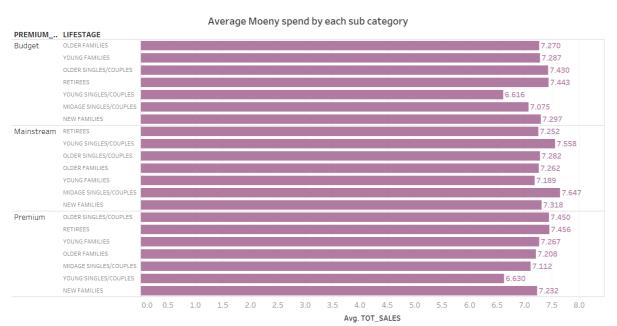
#### Result3 (Premium) :-

In Premium category Older Single/Couples and retirees more likely to buy Chips.

#### In [41]:

# <<<---- Average Moeny spend by each sub category ---->>>
Image('image7.png')

#### Out[41]:



 $\label{prop:control} \mbox{Average of TOT\_SALES for each LIFESTAGE broken down by PREMIUM\_CUSTOMER.}$ 

# Conclusion: Here we can clearly see that Customer's in every Lifestage in every Category are spending same money on average (ie. about 7 to 7.5 USD)

#### In [42]:

df.head()

#### Out[42]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	то
0	2018- 10-17	1	1000	1	5	Natural Chip Compny SeaSalt	2	
1	2019- 05-14	1	1307	348	66	CCs Nacho Cheese	3	
2	2018- 11-10	1	1307	346	96	WW Original Stacked Chips	2	
3	2019- 03-09	1	1307	347	54	CCs Original	1	
4	2019- 05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken	2	
4								•

#### In [43]:

```
# <<<--- Most sold Quantity --->>>
```

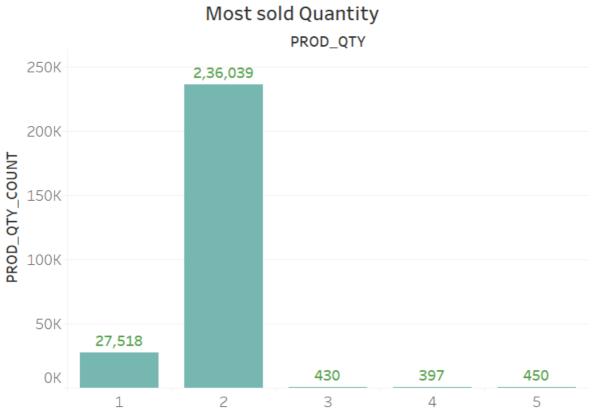
#### In [44]:

```
temp_df = df.groupby(by='PROD_QTY').count()
temp_df.reset_index(inplace=True)
temp_df.rename(columns={'TXN_ID': 'PROD_QTY_COUNT'}, inplace=True)
temp_df = temp_df.loc[:, ['PROD_QTY', 'PROD_QTY_COUNT']]
temp_df['PROD_QTY'] = temp_df['PROD_QTY'].astype(str)
temp_df.to_excel(excel_writer='Product_quantity_counts.xlsx', sheet_name='Sheet1')
```

#### In [45]:

```
Image('image8.png')
```

#### Out[45]:



Sum of PROD\_QTY\_COUNT for each PROD\_QTY.

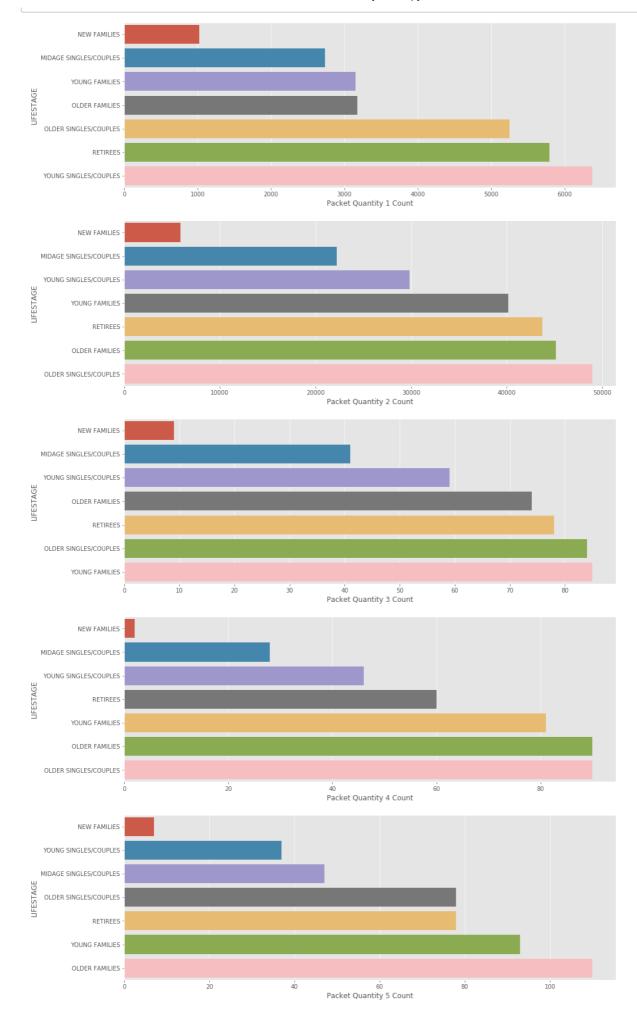
## Conclusion: - Here we clearly see that people mostly love to buy 2 packetes at a time.

```
In [46]:
```

```
# <<<---- Most sold quantity by LIFESTATGE ---->>>
```

#### In [47]:

```
temp_df = df.groupby(by='PROD_QTY')
# Group1 (1 Packet)
group1_df = temp_df.get_group(1)
temp_group1 = group1_df.groupby(by='LIFESTAGE').count()
temp_group1.sort_values('DATE', inplace=True)
x_count_group1 = temp_group1['DATE']
y_lifestage_group1 = temp_group1.index
# Group2 (2 Packet)
group2_df = temp_df.get_group(2)
temp_group2 = group2_df.groupby(by='LIFESTAGE').count()
temp_group2.sort_values('DATE', inplace=True)
x_count_group2 = temp_group2['DATE']
y_lifestage_group2 = temp_group2.index
# Group3 (3 Packet)
group3_df = temp_df.get_group(3)
temp_group3 = group3_df.groupby(by='LIFESTAGE').count()
temp_group3.sort_values('DATE', inplace=True)
x_count_group3 = temp_group3['DATE']
y_lifestage_group3 = temp_group3.index
# Group4 (4 Packet)
group4_df = temp_df.get_group(4)
temp_group4 = group4_df.groupby(by='LIFESTAGE').count()
temp_group4.sort_values('DATE', inplace=True)
x_count_group4 = temp_group4['DATE']
y_lifestage_group4 = temp_group4.index
# Group5 (5 Packet)
group5_df = temp_df.get_group(5)
temp_group5 = group5_df.groupby(by='LIFESTAGE').count()
temp_group5.sort_values('DATE', inplace=True)
x_count_group5 = temp_group5['DATE']
y_lifestage_group5 = temp_group5.index
# Plot the graphs
fig1, ax1 =plt.subplots(nrows=5, ncols=1, figsize=(15, 30))
sns.barplot(x=x_count_group1, y=y_lifestage_group1, ax=ax1[0])
ax1[0].set(xlabel="Packet Quantity 1 Count")
sns.barplot(x=x_count_group2, y=y_lifestage_group2, ax=ax1[1])
ax1[1].set(xlabel="Packet Quantity 2 Count")
sns.barplot(x=x_count_group3, y=y_lifestage_group3, ax=ax1[2])
ax1[2].set(xlabel="Packet Quantity 3 Count")
sns.barplot(x=x_count_group4, y=y_lifestage_group4, ax=ax1[3])
ax1[3].set(xlabel="Packet Quantity 4 Count")
sns.barplot(x=x_count_group5, y=y_lifestage_group5, ax=ax1[4])
ax1[4].set(xlabel="Packet Quantity 5 Count")
#save figure
plt.savefig('image9.png')
```



## Conclusion1 (Packet 1):-

Majority of persons that buy one packet are from the groups -> Old and Young (Singles/Couples), Retirees

## Conclusion2 (Packet 2) :-

Majority of persons that buy two packets are from the groups -> Older Singles/Couples and Families , Young Families, Retirees

### Conclusion3 (Packet 3):-

Majority of persons that buy three packets are from the groups -> Young and Older Families, Older Single/Couple, Retirees

## Conclusion4 (Packet 4):-

Majority of persons that buy four packets are from the groups -> Young and Older Families, Older Single/Couple

### Conclusion5 (Packet 5):-

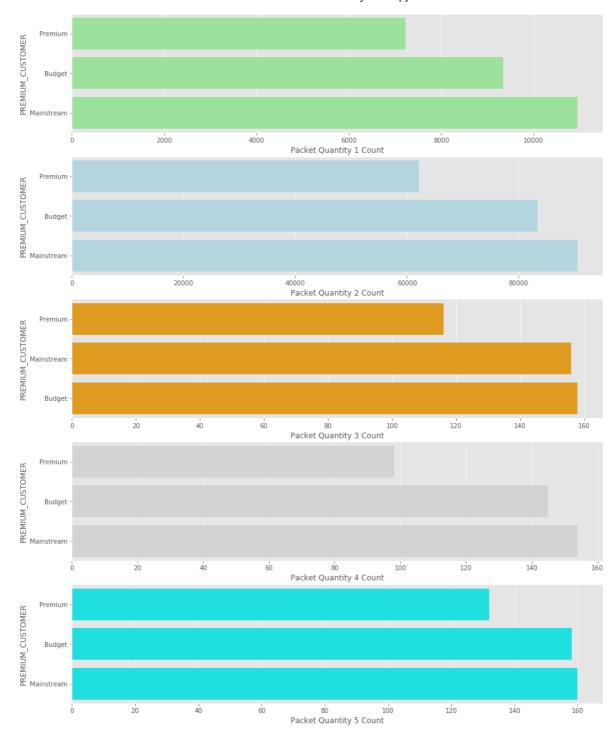
Majority of persons that buy five packets are from the groups -> Young and Older Families, Retirees

```
In [48]:
```

# <<<---- Most sold quantity by CATEGORY ---->>>

#### In [49]:

```
temp_df = df.groupby(by='PROD_QTY')
# Group1 (1 Packet)
group1_df = temp_df.get_group(1)
temp_group1 = group1_df.groupby(by='PREMIUM_CUSTOMER').count()
temp_group1.sort_values('DATE', inplace=True)
x_count_group1 = temp_group1['DATE']
y_category_group1 = temp_group1.index
# Group2 (2 Packet)
group2_df = temp_df.get_group(2)
temp_group2 = group2_df.groupby(by='PREMIUM_CUSTOMER').count()
temp_group2.sort_values('DATE', inplace=True)
x_count_group2 = temp_group2['DATE']
y_category_group2 = temp_group2.index
# Group3 (3 Packet)
group3_df = temp_df.get_group(3)
temp_group3 = group3_df.groupby(by='PREMIUM_CUSTOMER').count()
temp_group3.sort_values('DATE', inplace=True)
x_count_group3 = temp_group3['DATE']
y_category_group3 = temp_group3.index
# Group4 (4 Packet)
group4_df = temp_df.get_group(4)
temp_group4 = group4_df.groupby(by='PREMIUM_CUSTOMER').count()
temp_group4.sort_values('DATE', inplace=True)
x_count_group4 = temp_group4['DATE']
y_category_group4 = temp_group4.index
# Group5 (5 Packet)
group5_df = temp_df.get_group(5)
temp_group5 = group5_df.groupby(by='PREMIUM_CUSTOMER').count()
temp_group5.sort_values('DATE', inplace=True)
x_count_group5 = temp_group5['DATE']
y_category_group5 = temp_group5.index
# Plot the graphs
fig1, ax1 =plt.subplots(nrows=5, ncols=1, figsize=(15, 20))
sns.barplot(x=x_count_group1, y=y_category_group1, ax=ax1[0], color='lightgreen')
ax1[0].set(xlabel="Packet Quantity 1 Count")
sns.barplot(x=x_count_group2, y=y_category_group2, ax=ax1[1], color='lightblue')
ax1[1].set(xlabel="Packet Quantity 2 Count")
sns.barplot(x=x_count_group3, y=y_category_group3, ax=ax1[2], color='orange')
ax1[2].set(xlabel="Packet Quantity 3 Count")
sns.barplot(x=x_count_group4, y=y_category_group4, ax=ax1[3], color='lightgrey')
ax1[3].set(xlabel="Packet Quantity 4 Count")
sns.barplot(x=x_count_group5, y=y_category_group5, ax=ax1[4], color='cyan')
ax1[4].set(xlabel="Packet Quantity 5 Count")
#save figure
plt.savefig('image10.png')
```



## Conclusion: - Premium Customer buys less Chips in every segment of packet quantity.

## Final Summary...

- 1. Near Christmas sales of Chips go high.
- 2. Most packet sold are of average weight.
- 3. Older people more likely to buy chips followed by Young Families.
- 4. Retirees and single/Couples more likely to buy chips.
- 5. In Budget category everyone love to buy chips except mainstream single/couples.
- 6. In Mainstream Young/Single couples and families and retirees more likely to buy chips.
- 7. In Premium category Older Single/Couples and retirees more likely to buy Chips!.
- 8. Customer's in every Lifestage in every Category are spending same money on average (ie. about 7 to 7.5 USD).
- 9. People mostly love to buy 2 packetes at a time.
- 10.(a) Majority of persons that buy one packet are from the groups -> Old and Young (Singles/Couples), Retirees.
- 10(b). Majority of persons that buy two packets are from the groups -> Older Singles/Couples and Families, Young Families, Retirees.
- 10(c). Majority of persons that buy three packets are from the groups -> Young and Older Families, Older Single/Couple, Retirees.

10(d). Majority of persons that buy four packets are from the groups -> Young and Older Families, Older Single/Couple.

10(e). Majority of persons that buy five packets are from the groups -> Young and Older Families, Retirees.

Basically the Customers that are old and have families buys 3 to 4 packets at a time and Singles/Couples buy 1 to 2 packets at a time.

11. Premium Customer seems to buy less Chips in every segment of packet quantity.