Task 1

Data Preparation and customer analysis

In [28]:

```
#imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

In [29]:

```
from plotly.offline import init_notebook_mode, iplot
init_notebook_mode(connected=True)
import plotly.offline as offline
offline.init_notebook_mode()
import cufflinks as cf
cf.go_offline()
```

In [30]:

```
#reading data
purchase=pd.read_csv("QVI_purchase_behaviour.csv");
purchase.head(2)
```

Out[30]:

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER
0	1000	YOUNG SINGLES/COUPLES	Premium
1	1002	YOUNG SINGLES/COUPLES	Mainstream

In [31]:

```
transaction=pd.read_excel("QVI_transaction_data.xlsx")
transaction.head(2)
```

Out[31]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY
0	43390	1	1000	1	5	Natural Chip Compny SeaSalt175g	
1	43599	1	1307	348	66	CCs Nacho Cheese 175g	

Transaction

In [32]:

```
#transforming date column
transaction["DATE"]=pd.to_datetime(transaction["DATE"], origin = "1899-12-30",u
```

In [33]:

```
transaction["PROD_NAME"].describe()
```

Out[33]:
```
count                                   264836
unique                                     114
top       Kettle Mozzarella   Basil & Pesto 175g
freq                                      3304
Name: PROD_NAME, dtype: object
```

In [34]:
```
#finding the most frequest words
import collections
freq=collections.Counter([j  for s in transaction["PROD_NAME"] for j in s.split
```

In [35]:
```
#sorting in decreasing order of the frequency of words
fre=pd.DataFrame([freq.keys(),freq.values()],index=['Word','Frequency']).transp
```

In [36]:
```
# removing useless words like '170g'
fre=fre[[ s[0] not in  ['0','1','2','3','4','5','6','7','8','9','&'] for s in f
# most frequent words
fre.head()
```

Out[36]:

	Word	Frequency
11	Chips	49770
16	Kettle	41288
8	Smiths	28860
29	Salt	27976
6	Cheese	27890

In [37]:
```
#dropping salsa items
transaction.drop(transaction[[("Salsa" in s)  for s in transaction['PROD_NAME']
```

In [38]:
```
transaction[[("Salsa" in s)  for s in transaction['PROD_NAME']]]
```

Out[38]:

DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY

In [39]:
```
#details about transaction dataset
```

In [40]:
```
transaction.describe()
```

Out[40]:

	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_QTY	
count	246742.000000	2.467420e+05	2.467420e+05	246742.000000	246742.000000	2
mean	135.051098	1.355310e+05	1.351311e+05	56.351789	1.908062	
std	76.787096	8.071528e+04	7.814772e+04	33.695428	0.659831	
min	1.000000	1.000000e+03	1.000000e+00	1.000000	1.000000	
25%	70.000000	7.001500e+04	6.756925e+04	26.000000	2.000000	
50%	130.000000	1.303670e+05	1.351830e+05	53.000000	2.000000	

75%	203.000000	2.030840e+05	2.026538e+05	87.000000	2.000000
max	272.000000	2.373711e+06	2.415841e+06	114.000000	200.000000

In [41]:

```
transaction.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 246742 entries, 0 to 264835
Data columns (total 8 columns):
DATE              246742 non-null datetime64[ns]
STORE_NBR         246742 non-null int64
LYLTY_CARD_NBR    246742 non-null int64
TXN_ID            246742 non-null int64
PROD_NBR          246742 non-null int64
PROD_NAME         246742 non-null object
PROD_QTY          246742 non-null int64
TOT_SALES         246742 non-null float64
dtypes: datetime64[ns](1), float64(1), int64(5), object(1)
memory usage: 16.9+ MB
```

In [42]:

```
#number of nulls in each column
transaction.isna().sum()
```

Out[42]:

```
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
```

Removing anomalies

In [43]:

```
#product quantity
```

In [44]:

```
transaction['PROD_QTY'].describe()
```

Out[44]:

```
count    246742.000000
mean          1.908062
std           0.659831
min           1.000000
25%           2.000000
50%           2.000000
75%           2.000000
max         200.000000
Name: PROD_QTY, dtype: float64
```

In [45]:

```
transaction[transaction['PROD_QTY']>5]
```

Out[45]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD
69762	2018-08-19	226	226000	226201	4	Dorito Corn Chp Supreme 380g	

69763	2019-05-20	226	226000	226210	4	Dorito Corn Chp Supreme 380g

In [46]:
```
transaction.drop(labels=transaction[transaction['PROD_QTY']==200].index,inplace
#transaction.drop(labels=transaction[transaction['TOT_SALES']>600].index,inplac
#transaction.drop(labels=transaction[transaction['TXN_ID']>1500000].index,inpla
```

In [47]:
```
#missing dates
```

In [48]:
```
ts=transaction.groupby('DATE').count()
ts.head()
```

Out[48]:

DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	T
2018-07-01	663	663	663	663	663	663	
2018-07-02	650	650	650	650	650	650	
2018-07-03	674	674	674	674	674	674	
2018-07-04	669	669	669	669	669	669	
2018-07-05	660	660	660	660	660	660	

In [49]:
```
#missing date
set(pd.date_range('2018-07-01', end='2019-06-30',freq='D'))-set((ts.index))
```

Out[49]:
```
{Timestamp('2018-12-25 00:00:00', freq='D')}
```

In [50]:
```
ts.loc['2018-12-25']=np.nan#=ts.mean().apply(int)
```

In [51]:
```
ts[ts.index=='2018-12-25']
```

Out[51]:

DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	T
2018-12-25	NaN	NaN	NaN	NaN	NaN	NaN	

In [53]:
```
#plot showing missing date
ts['TXN_ID'].iplot(kind='bar',xTitle='Day',yTitle= "Number of transactions", ti
```

In [27]:

```python
#Adding features
```

In [56]:

```python
def fun(s):
    a=[]
    for i in s:
        if i in ['0','1','2','3','4','5','6','7','8','9']:
            a.append(i)
    return int("".join(a))
```

In [57]:

```python
transaction['PACKAGE_SIZE']=transaction['PROD_NAME'].apply(fun)
transaction.head(5)
```

Out[57]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_C
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	

In [58]:

```python
transaction['BRAND']=[s.split()[0] for s in transaction['PROD_NAME']]
transaction['BRAND'].replace('Dorito','Doritos',inplace=True)
transaction['BRAND'].replace('Infzns','Infuzions',inplace=True)
transaction['BRAND'].replace('Smith','Smiths',inplace=True)
transaction['BRAND'].replace('Snbts','Sunbites',inplace=True)
transaction['BRAND'].replace('Red','RRD',inplace=True)
transaction['BRAND'].replace('Old','Old El Paso',inplace=True)
transaction['BRAND'].replace('WW','Woolworths',inplace=True)
transaction['BRAND'].replace('Natural','NCC',inplace=True)
```

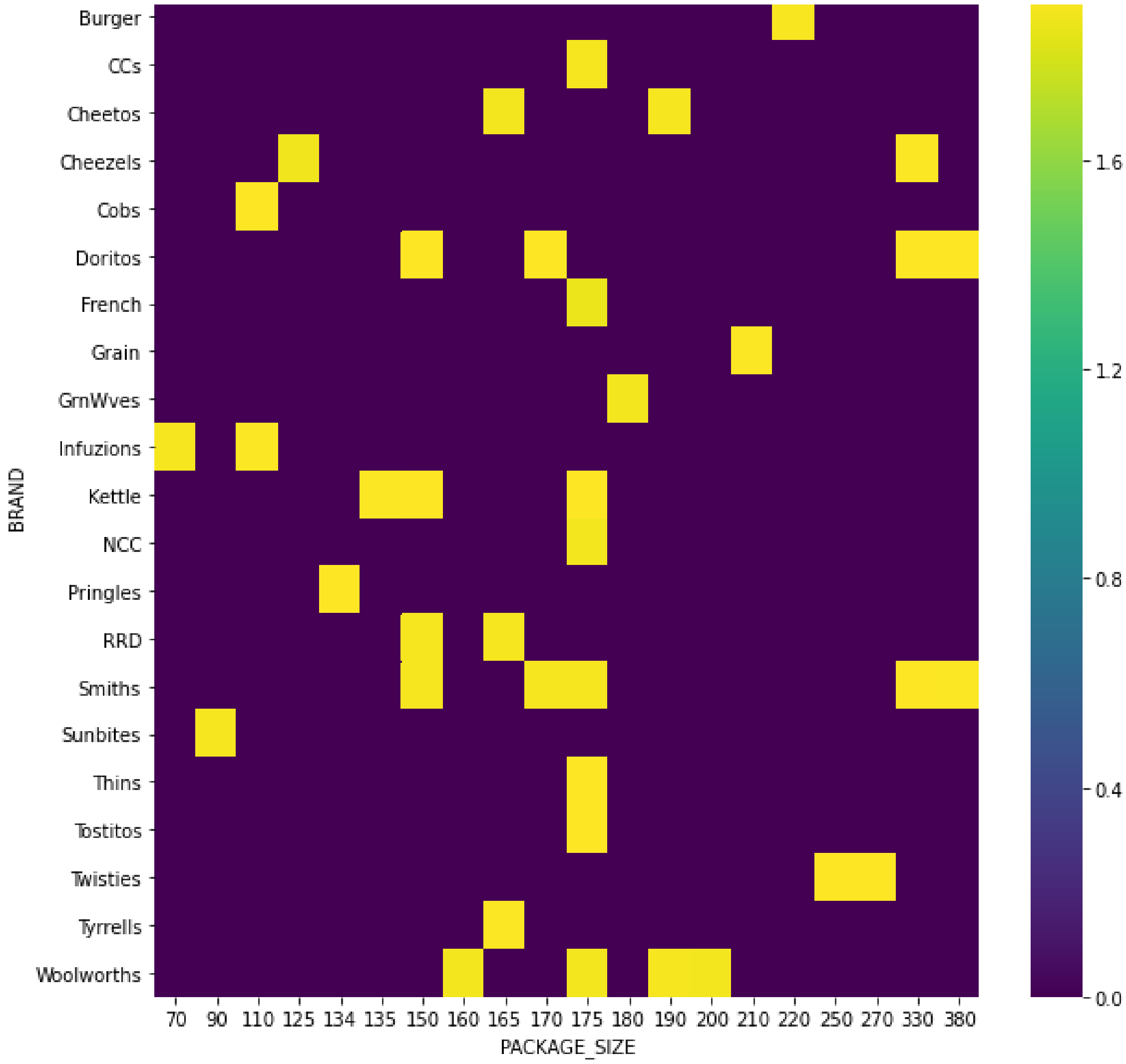
In [111…

```python
#Histogram for brands
transaction['BRAND'].iplot(kind='hist',xTitle='Brand',yTitle='Packets sold',tit
```

In [60]:

```python
#heatmap showing packet quantity mostly bought according to brand and packet si
plt.figure(figsize=(10,10))
sns.heatmap(pd.pivot_table(data=transaction,index='BRAND',columns='PACKAGE_SIZE
```

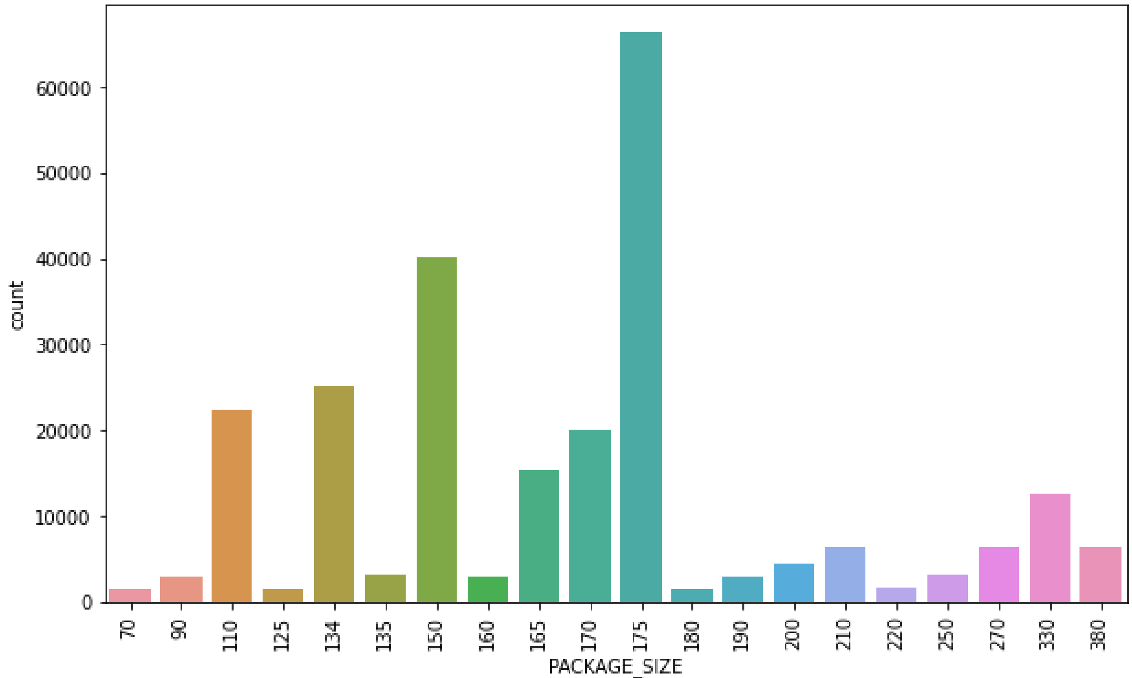
Out[60]: <AxesSubplot:xlabel='PACKAGE_SIZE', ylabel='BRAND'>



In [61]:

```
#histogram of packet size
plt.figure(figsize=(10,6))
plt.xticks(rotation=90)
sns.countplot(transaction['PACKAGE_SIZE'])
```

Out[61]: <AxesSubplot:xlabel='PACKAGE_SIZE', ylabel='count'>

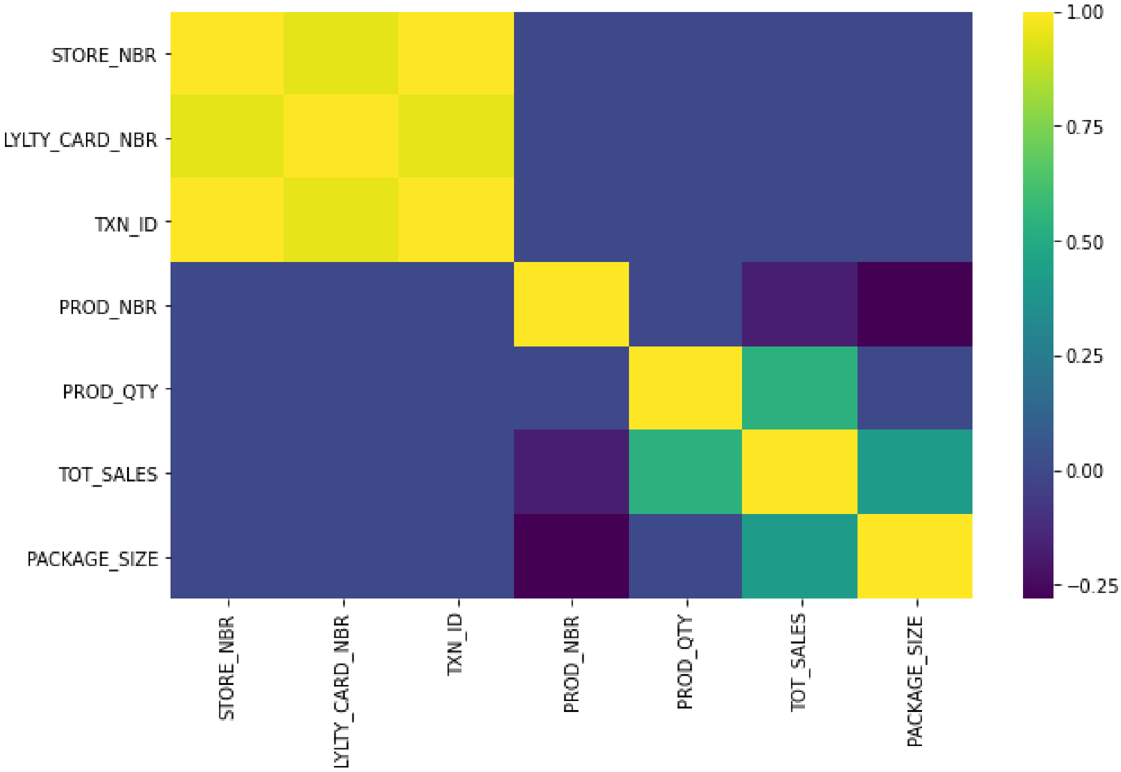


In [62]:

In [62]:

```python
#correlation heatmap
plt.figure(figsize=(10,6))
sns.heatmap(transaction.corr(),cmap='viridis')
```

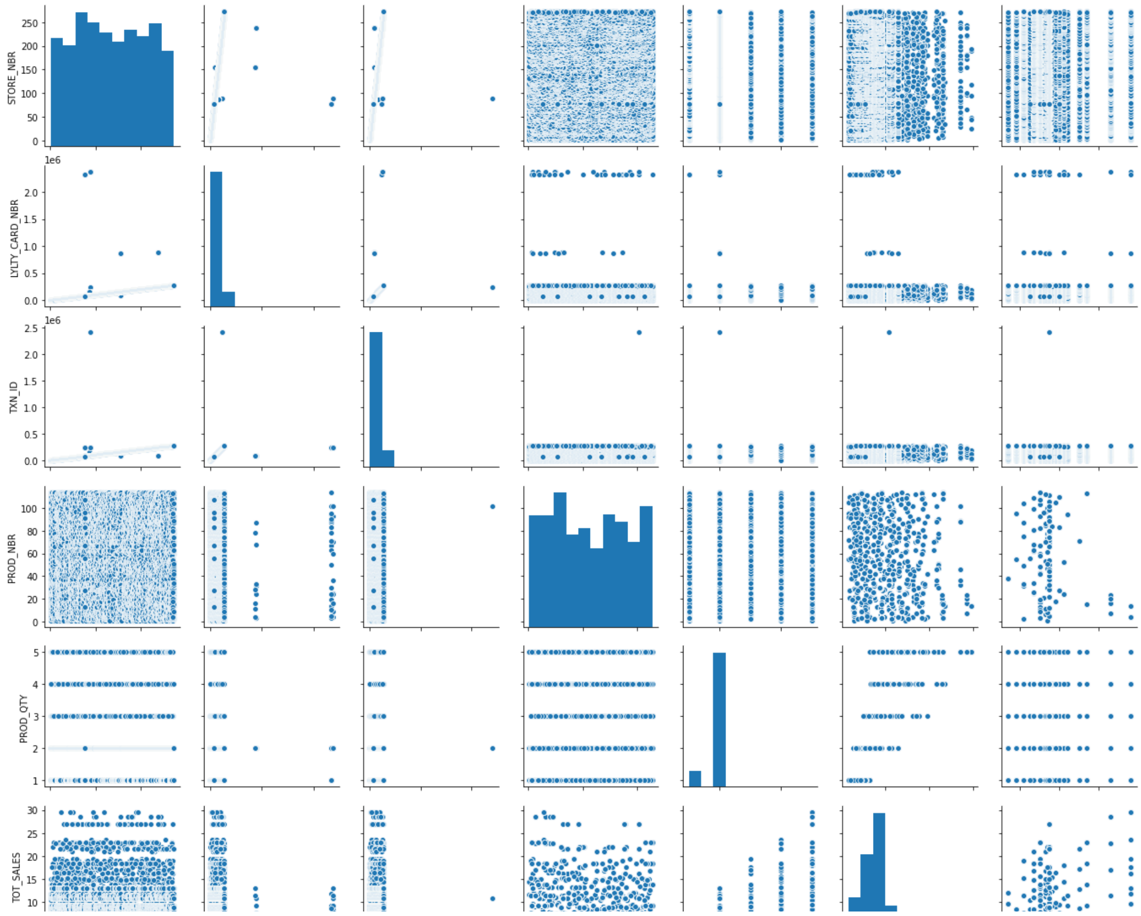
Out[62]: <AxesSubplot:>

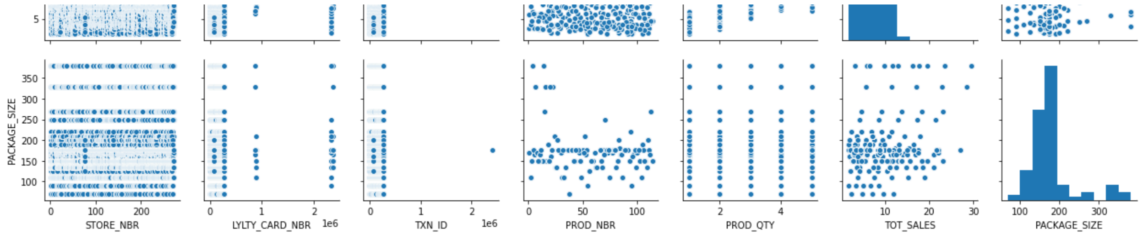


In [35]:

```python
#pairplot
sns.pairplot(data=transaction[transaction.columns.drop('PROD_NAME')])
```

Out[35]: <seaborn.axisgrid.PairGrid at 0x257ba3c6f08>





Purchase

In [63]:
```
purchase.head(3)
```

Out[63]:

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

In [64]:
```
purchase['LYLTY_CARD_NBR'].nunique()
```

Out[64]: 72637

In [65]:
```
purchase.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 72637 entries, 0 to 72636
Data columns (total 3 columns):
LYLTY_CARD_NBR      72637 non-null int64
LIFESTAGE           72637 non-null object
PREMIUM_CUSTOMER    72637 non-null object
dtypes: int64(1), object(2)
memory usage: 1.7+ MB
```

In [66]:
```
purchase.describe(include='all')
```

Out[66]:

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER
count	7.263700e+04	72637	72637
unique	NaN	7	3
top	NaN	RETIREES	Mainstream
freq	NaN	14805	29245
mean	1.361859e+05	NaN	NaN
std	8.989293e+04	NaN	NaN
min	1.000000e+03	NaN	NaN
25%	6.620200e+04	NaN	NaN
50%	1.340400e+05	NaN	NaN
75%	2.033750e+05	NaN	NaN
max	2.373711e+06	NaN	NaN

In [67]:

```
#Lifestage distribution among customers
purchase['LIFESTAGE'].iplot(kind='hist')
```

In [68]:

```
#Premium customer distribution among customers
purchase['PREMIUM_CUSTOMER'].iplot(kind='hist')
```

In [69]:

```
purchase.isna().sum()
```

Out[69]:

```
LYLTY_CARD_NBR      0
LIFESTAGE           0
PREMIUM_CUSTOMER    0
dtype: int64
```

joining datasets

In [70]:

```
finaldf=pd.merge(transaction,purchase,on='LYLTY_CARD_NBR')
finaldf.head(2)
```

Out[70]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY
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

In [71]:

```
finaldf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 246740 entries, 0 to 246739
Data columns (total 12 columns):
DATE                246740 non-null datetime64[ns]
STORE_NBR           246740 non-null int64
LYLTY_CARD_NBR      246740 non-null int64
TXN_ID              246740 non-null int64
PROD_NBR            246740 non-null int64
PROD_NAME           246740 non-null object
PROD_QTY            246740 non-null int64
TOT_SALES           246740 non-null float64
PACKAGE_SIZE        246740 non-null int64
BRAND               246740 non-null object
LIFESTAGE           246740 non-null object
PREMIUM_CUSTOMER    246740 non-null object
dtypes: datetime64[ns](1), float64(1), int64(6), object(4)
memory usage: 24.5+ MB
```

In [72]:

```
finaldf.isna().sum()
```

Out[72]:

```
DATE                0
```

```
STORE_NBR           0
LYLTY_CARD_NBR      0
TXN_ID              0
PROD_NBR            0
PROD_NAME           0
PROD_QTY            0
TOT_SALES           0
PACKAGE_SIZE        0
BRAND               0
LIFESTAGE           0
PREMIUM_CUSTOMER    0
dtype: int64
```

In [73]:

```
finaldf.to_csv('Final.csv')
```

In [74]:

```
finaldf[['TOT_SALES','PREMIUM_CUSTOMER']].groupby('PREMIUM_CUSTOMER').sum().sor
```

Out[74]:

PREMIUM_CUSTOMER	TOT_SALES
Mainstream	700865.40
Budget	631406.85
Premium	472905.45

In [75]:

```
#Who spends the most on chips (total sales), describing customers by lifestage
#how premium their general purchasing behaviour is
a=finaldf[['LIFESTAGE','PREMIUM_CUSTOMER','TOT_SALES']].groupby(['PREMIUM_CUSTC
a.sort_values('TOT_SALES',ascending=False)
```

Out[75]:

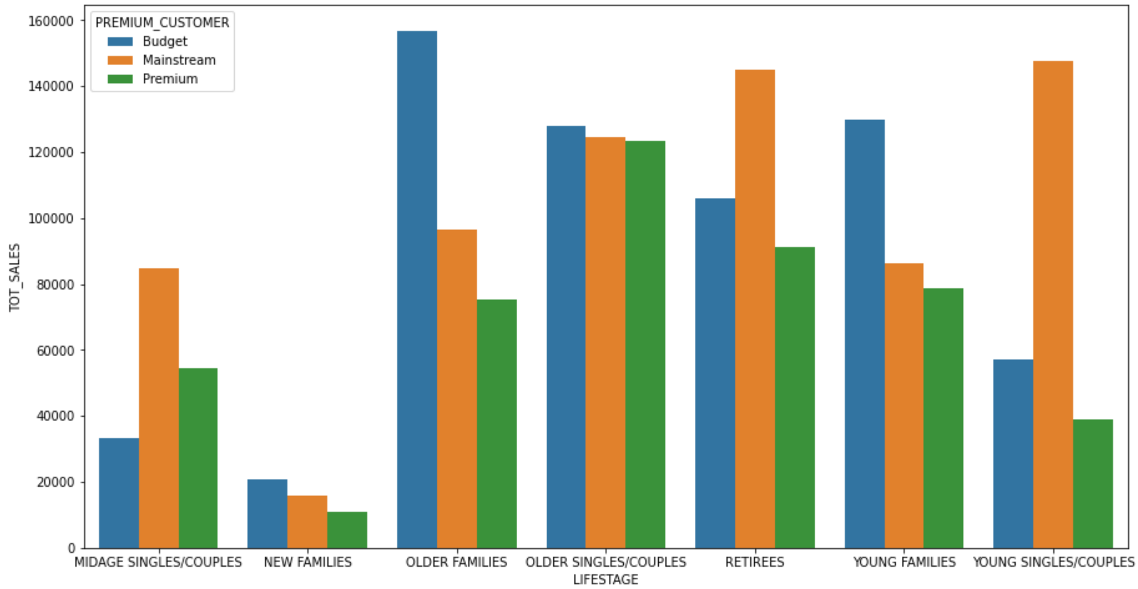
PREMIUM_CUSTOMER	LIFESTAGE	TOT_SALES
Budget	OLDER FAMILIES	156863.75
Mainstream	YOUNG SINGLES/COUPLES	147582.20
	RETIREES	145168.95
Budget	YOUNG FAMILIES	129717.95
	OLDER SINGLES/COUPLES	127833.60
Mainstream	OLDER SINGLES/COUPLES	124648.50
Premium	OLDER SINGLES/COUPLES	123537.55
Budget	RETIREES	105916.30
Mainstream	OLDER FAMILIES	96413.55
Premium	RETIREES	91296.65
Mainstream	YOUNG FAMILIES	86338.25
	MIDAGE SINGLES/COUPLES	84734.25
Premium	YOUNG FAMILIES	78571.70
	OLDER FAMILIES	75242.60
Budget	YOUNG SINGLES/COUPLES	57122.10

Budget	YOUNG SINGLES/COUPLES	57122.10
Premium	MIDAGE SINGLES/COUPLES	54443.85
	YOUNG SINGLES/COUPLES	39052.30
Budget	MIDAGE SINGLES/COUPLES	33345.70
	NEW FAMILIES	20607.45
Mainstream	NEW FAMILIES	15979.70
Premium	NEW FAMILIES	10760.80

In [106…

```
plt.figure(figsize=(15,8))
sns.barplot(y=a.reset_index()['TOT_SALES'],x=a.reset_index()['LIFESTAGE'],hue=a
```

Out[106… <AxesSubplot:xlabel='LIFESTAGE', ylabel='TOT_SALES'>



In [107…

```
a.iplot(title="Sales per segment",yTitle='Total sales',xTitle='Segment')
```

In [50]:

```
# How many customers are in each segment
b=purchase.groupby(['PREMIUM_CUSTOMER','LIFESTAGE']).count()
b.columns=['CUSTOMER_COUNT']
b.sort_values('CUSTOMER_COUNT',ascending=False)
```

Out[50]:

PREMIUM_CUSTOMER	LIFESTAGE	CUSTOMER_COUNT
Mainstream	YOUNG SINGLES/COUPLES	8088
	RETIREES	6479
	OLDER SINGLES/COUPLES	4930
Budget	OLDER SINGLES/COUPLES	4929
Premium	OLDER SINGLES/COUPLES	4750
	OLDER FAMILIES	4675
Budget	RETIREES	4454

	YOUNG FAMILIES	4017
Premium	RETIREES	3872
Budget	YOUNG SINGLES/COUPLES	3779
	MIDAGE SINGLES/COUPLES	3340
Mainstream	OLDER FAMILIES	2831
	YOUNG FAMILIES	2728
	YOUNG SINGLES/COUPLES	2574
Premium	YOUNG FAMILIES	2433
	MIDAGE SINGLES/COUPLES	2431
	OLDER FAMILIES	2274
Budget	MIDAGE SINGLES/COUPLES	1504
	NEW FAMILIES	1112
Mainstream	NEW FAMILIES	849
Premium	NEW FAMILIES	588

In [51]:

```
b.iplot(title="Number of customers per segment",yTitle='No of Customers',xTitle
```

In [52]:

```
#  This contributes to there being more sales to these customer segments but
# this is not a major driver for the Budget - Older families segment.
# Higher sales may also be driven by more units of chips being bought per custo
```

In [53]:

```
#How many chips are bought per customer by segment
c=finaldf[['LIFESTAGE','PREMIUM_CUSTOMER','TOT_SALES']].groupby(['LIFESTAGE','P
c.sort_values('TOT_SALES',ascending=False).head(5)
```

Out[53]:

LIFESTAGE	PREMIUM_CUSTOMER	TOT_SALES
OLDER FAMILIES	Budget	21514
RETIREES	Mainstream	19970
YOUNG SINGLES/COUPLES	Mainstream	19544
YOUNG FAMILIES	Budget	17763
OLDER SINGLES/COUPLES	Budget	17172

In [54]:

```
c.iplot(title="Number of packets sold per segment",yTitle='No of Packets',xTitl
```

In [57]:

```
#  The customer's total spend over the period
# to understand what proportion of their grocery spend is on chips
transaction1=pd.read_excel("QVI_transaction_data.xlsx")
```

```
totsalespercust=transaction[['LYLTY_CARD_NBR','TOT_SALES']].groupby(['LYLTY_CA
ratio=finaldf[['LYLTY_CARD_NBR','TOT_SALES']].merge(totsalespercust,on='LYLTY_C
ratio['RATIO']=ratio['TRAN_SALE']/ratio['CUST_TOT_SALE']
ratio.sort_values('RATIO')
```

Out[57]:

	LYLTY_CARD_NBR	TRAN_SALE	CUST_TOT_SALE	RATIO
174208	152094	1.9	112.1	0.016949
75460	48155	1.9	100.7	0.018868
174557	168140	1.7	86.5	0.019653
16284	104061	1.7	85.9	0.019790
30772	55244	1.7	85.7	0.019837
...	...	...	...	...
163956	49312	11.4	11.4	1.000000
163855	47486	7.4	7.4	1.000000
163852	47465	10.8	10.8	1.000000
162683	12139	8.6	8.6	1.000000
246739	272380	8.8	8.8	1.000000

246740 rows × 4 columns

In [92]:

```
#  Proportion of customers in each customer segment overall to compare against
# mix of customers who purchase chips
e=finaldf[['LIFESTAGE','PREMIUM_CUSTOMER','TOT_SALES']].groupby(['PREMIUM_CUSTO
e["TOT_SALES"]/(e['TOT_SALES'].sum())
```

Out[92]:

```
PREMIUM_CUSTOMER  LIFESTAGE
Budget            MIDAGE SINGLES/COUPLES    0.019012
                  NEW FAMILIES              0.011445
                  OLDER FAMILIES            0.087193
                  OLDER SINGLES/COUPLES     0.069596
                  RETIREES                  0.057652
                  YOUNG FAMILIES            0.071991
                  YOUNG SINGLES/COUPLES     0.034745
Mainstream        MIDAGE SINGLES/COUPLES    0.044966
                  NEW FAMILIES              0.008855
                  OLDER FAMILIES            0.053664
                  OLDER SINGLES/COUPLES     0.069146
                  RETIREES                  0.080935
                  YOUNG FAMILIES            0.048419
                  YOUNG SINGLES/COUPLES     0.079209
Premium           MIDAGE SINGLES/COUPLES    0.030850
                  NEW FAMILIES              0.006031
                  OLDER FAMILIES            0.042162
                  OLDER SINGLES/COUPLES     0.067115
                  RETIREES                  0.049591
                  YOUNG FAMILIES            0.043706
                  YOUNG SINGLES/COUPLES     0.023717
Name: TOT_SALES, dtype: float64
```

In [55]:

```
# What's the average chip price by customer segment
finaldf['CHIP_PRICE']=finaldf['TOT_SALES']/finaldf['PROD_QTY']
d=finaldf[['LIFESTAGE','PREMIUM_CUSTOMER','CHIP_PRICE']].groupby(['PREMIUM_CUST
d.sort_values("CHIP_PRICE",ascending=False)
```

Out[55]:

PREMIUM_CUSTOMER	LIFESTAGE	CHIP_PRICE
Mainstream	YOUNG SINGLES/COUPLES	4.065642
	MIDAGE SINGLES/COUPLES	3.994241
Budget	RETIREES	3.924404
Premium	RETIREES	3.920942
Budget	NEW FAMILIES	3.917688
Mainstream	NEW FAMILIES	3.916133
Premium	OLDER SINGLES/COUPLES	3.893182
Budget	OLDER SINGLES/COUPLES	3.882096
Premium	NEW FAMILIES	3.872110
Mainstream	RETIREES	3.844294
	OLDER SINGLES/COUPLES	3.814665
Premium	MIDAGE SINGLES/COUPLES	3.770698
	YOUNG FAMILIES	3.762150
Budget	YOUNG FAMILIES	3.760737
	OLDER FAMILIES	3.745340
	MIDAGE SINGLES/COUPLES	3.743328
Mainstream	OLDER FAMILIES	3.737077
	YOUNG FAMILIES	3.724533
Premium	OLDER FAMILIES	3.717000
	YOUNG SINGLES/COUPLES	3.665414
Budget	YOUNG SINGLES/COUPLES	3.657366

In [56]:

```
d.iplot(title="Avg pay per packet per segment",yTitle='Avg Payment',xTitle='Seg
```

In [59]:

```
#t-test
```

In [60]:

```
from scipy import stats
#Mainstream vs premium
stats.ttest_ind([4.065642,3.994241],[3.770698,3.665414])
```

Out[60]: Ttest_indResult(statistic=4.903408005498769, pvalue=0.039164352682153285)

In [61]:

```
#Mainstream vs budget
stats.ttest_ind([4.065642,3.994241],[3.657366,3.743328])
```

Out[61]: Ttest_indResult(statistic=5.898899732826305, pvalue=0.027555775534860754)

In [62]:

```
# The t-test results in a p-value of 0.03 and 0.02 , i.e. the unit price for ma
# young and mid-age singles and couples ARE significantly higher than
# that of budget or premium, young and midage singles and couples.
```

In [63]:

```
#Now we are focussing on the mainstream, young and mid-age singles and couples
# brands that these two customer segments prefer more than others
```

In [64]:

```
midage=finaldf[(finaldf['PREMIUM_CUSTOMER']=='Mainstream') & (finaldf['LIFESTAG
young=finaldf[(finaldf['PREMIUM_CUSTOMER']=='Mainstream') & (finaldf['LIFESTAGE
print(f"MIDAGE SINGLES/COUPLES\n{midage['BRAND'].value_counts().head(5)}")
print(f"YOUNG SINGLES/COUPLES\n{young['BRAND'].value_counts().head(5)}")
```

```
MIDAGE SINGLES/COUPLES
Kettle       2136
Smiths       1276
Doritos      1210
Pringles     1159
Infuzions     679
Name: BRAND, dtype: int64
YOUNG SINGLES/COUPLES
Kettle       3844
Doritos      2379
Pringles     2315
Smiths       1921
Infuzions    1250
Name: BRAND, dtype: int64
```

In [65]:

```
#Kettle, Smiths and Doritos are popular among MIDAGE and Kettle, Pringles and D
```

In [66]:

```
print(f"MIDAGE SINGLES/COUPLES\n{midage['PACKAGE_SIZE'].value_counts().head(5)}
print(f"YOUNG SINGLES/COUPLES\n{young['PACKAGE_SIZE'].value_counts().head(5)}")
```

```
MIDAGE SINGLES/COUPLES
175    2975
150    1777
134    1159
110    1124
170     882
Name: PACKAGE_SIZE, dtype: int64
YOUNG SINGLES/COUPLES
175    4997
150    3080
134    2315
110    2051
170    1575
Name: PACKAGE_SIZE, dtype: int64
```

In [67]:

```
#both the segments buy 175g,150g and 134  packets mostly
```

Association rules

In [68]:

```
from mlxtend.frequent_patterns import apriori, association_rules,fpgrowth
```

In [76]:

```
basket=finaldf.groupby(['LYLTY_CARD_NBR','BRAND'])['PROD_QTY'].sum().unstack().
basket
```

Out[76]:

BRAND	Burger	CCs	Cheetos	Cheezels	Cobs	Doritos	French	Grain	GrnW
LYLTY_CARD_NBR									
1000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
1002	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
1003	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
1004	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
1005	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	
2370651	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	
2370701	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	
2370751	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2370961	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2373711	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

71287 rows × 21 columns

In [77]:

```
def reducer(x):
    if x <= 0:
        return 0
    else:
        return 1
basket=basket.applymap(reducer)
basket
```

Out[77]:

BRAND	Burger	CCs	Cheetos	Cheezels	Cobs	Doritos	French	Grain	GrnW
LYLTY_CARD_NBR									
1000	0	0	0	0	0	0	0	0	
1002	0	0	0	0	0	0	0	0	
1003	0	0	0	0	0	0	0	1	
1004	0	0	0	0	0	0	0	0	
1005	0	0	1	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	
2370651	0	0	0	0	0	1	0	0	
2370701	0	0	0	0	0	0	0	1	
2370751	0	0	0	0	0	0	0	0	
2370961	0	0	0	0	0	0	0	0	
2373711	0	0	0	0	0	0	0	0	

71287 rows × 21 columns

In [87]:

```
frequent=apriori(basket,0.1,use_colnames=True)
frequent
```

Out[87]:

	support	itemsets
0	0.125745	(Cobs)
1	0.290446	(Doritos)
2	0.177311	(Infuzions)
3	0.423303	(Kettle)
4	0.289772	(Pringles)
5	0.180103	(RRD)
6	0.314896	(Smiths)
7	0.176624	(Thins)
8	0.122884	(Tostitos)
9	0.122449	(Twisties)
10	0.139661	(Woolworths)
11	0.136420	(Kettle, Doritos)
12	0.135452	(Pringles, Kettle)
13	0.135130	(Kettle, Smiths)

In [88]:

```
association_rules(frequent,metric='lift',min_threshold=1).sort_values(['support
```

Out[88]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift
1	(Doritos)	(Kettle)	0.290446	0.423303	0.136420	0.469693	1.109591
0	(Kettle)	(Doritos)	0.423303	0.290446	0.136420	0.322276	1.109591
2	(Pringles)	(Kettle)	0.289772	0.423303	0.135452	0.467444	1.104279
3	(Kettle)	(Pringles)	0.423303	0.289772	0.135452	0.319989	1.104279
5	(Smiths)	(Kettle)	0.314896	0.423303	0.135130	0.429125	1.013754
4	(Kettle)	(Smiths)	0.423303	0.314896	0.135130	0.319227	1.013754

In [93]:

```
#Therefore if someone buys Doritos Kettle can be recommended and vice-versa. Sa
```

Thanks