

Quantum Data Analytics Project

Section 1

Import packages and read datafiles

```
In [458]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from plotly import __version__
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
import cufflinks as cf
%matplotlib inline

from datetime import datetime
import xlrd

from collections import Counter

from scipy.stats import ttest_ind

from apyori import apriori
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules
```

```
In [224]: customer = pd.read_csv('QVI_purchase_behaviour.csv')
transaction = pd.read_excel('QVI_transaction_data.xlsx')
```

Exploratory Data Analysis

Data Preprocessing

```
In [225]: customer = customer.dropna()
transaction = transaction.dropna()
```

Examine transaction data

Convert Excel Date into Python Date

```
In [255]: transaction['DATE'] = transaction['DATE'].apply(lambda s: xlrd.xldate.xldate_as_datetime(s, transaction.transaction))
```

Out[255]:

	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
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
...
264831	2019-03-09	272	272319	270088	89	Kettle Sweet Chilli And Sour Cream 175g	2
264832	2018-08-13	272	272358	270154	74	Tostitos Splash Of Lime 175g	1
264833	2018-11-06	272	272379	270187	51	Doritos Mexicana 170g	2
264834	2018-12-27	272	272379	270188	42	Doritos Corn Chip Mexican Jalapeno 150g	2
264835	2018-09-22	272	272380	270189	74	Tostitos Splash Of Lime 175g	2

264836 rows × 9 columns

Discover the most common words in product names

```
In [256]: # Remove special characters in product names

import re

product = transaction['PROD_NAME']

cleaned_name = []
for string in product:
    string = re.sub(r'\\.', '', string)      # Remove all \n \t etc..
    string = re.sub(r'^\w\s*', '', string)    # Remove anything not a digit, letter

    cleaned_name.append(string)

transaction['PROD_NAME2'] = cleaned_name
```

```
In [257]: unique_products = []
for p in transaction['PROD_NAME2']:
    if p not in unique_products:
        unique_products.append(p)
```

```
In [258]: # Count the most common words in all product names
count_lists = []

for w in unique_products:
    word = w.split()[:-1]
    count_lists.append(word)

counter = Counter(count_lists[0])
for i in count_lists[1:]:
    counter.update(i)

counter.most_common(10)
```

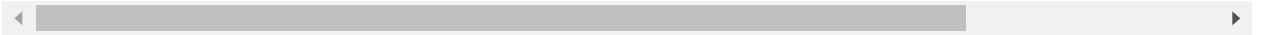
```
Out[258]: [('Chips', 21),
            ('Smiths', 16),
            ('Crinkle', 14),
            ('Cut', 14),
            ('Kettle', 13),
            ('Cheese', 12),
            ('Salt', 11),
            ('Original', 10),
            ('Chip', 9),
            ('Salsa', 9)]
```

Check for outliers

```
In [259]: sort_by_quant1 = transaction.sort_values('PROD_QTY',ascending=False)
sort_by_quant1.head()
```

Out[259]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	1
69762	2018-08-19	226	226000	226201	4	Dorito Corn Chp Supreme 380g	200	
69763	2019-05-20	226	226000	226210	4	Dorito Corn Chp Supreme 380g	200	
217237	2019-05-18	201	201060	200202	26	Pringles Sweet&Spicy BBQ 134g	5	
238333	2018-08-14	219	219004	218018	25	Pringles SourCream Onion 134g	5	
238471	2019-05-19	261	261331	261111	87	Infuzions BBQ Rib Prawn Crackers 110g	5	



```
In [260]: # There are two transactions where 200 packets of chips are bought in one transac
# and both of these transactions were by the same customer.

# It looks like this customer has only had the two transactions over the year
# and is not an ordinary retail customer. The customer might be buying chips for
# We'll remove this loyalty card number from further analysis.![image.png]
```

Filtering out outliers

```
In [261]: i = transaction.loc[transaction['PROD_QTY']>50].index
transaction_new = transaction.drop(i)
transaction_new.head()
```

Out[261]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_
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	

```
In [262]: sort_by_quant2 = transaction_new.sort_values('PROD_QTY',ascending=False)
sort_by_quant2.head()
```

Out[262]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY
5415	2018-08-20	236	236116	239252	12	Natural Chip Co Tmato Hrb&Spce 175g	5
32796	2019-05-18	236	236033	238735	59	Old El Paso Salsa Dip Tomato Med 300g	5
5107	2018-08-17	54	54225	48172	46	Kettle Original 175g	5
80732	2019-05-18	49	49309	45816	30	Doritos Corn Chips Cheese Supreme 170g	5
32762	2018-08-19	227	227046	228561	100	Smiths Crinkle Cut Chips Chs&Onion170g	5

Select only the "chips" products to evaluate

```
In [263]: j = transaction.loc[transaction['PROD_NAME'].str.contains("Chips", na=False)].index
chips = transaction.iloc[j]
chips.head()
```

Out[263]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_
2	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	
6	2019-05-16	4	4149	3333	16	Smiths Crinkle Chips Salt & Vinegar 330g	1	
10	2019-05-17	7	7215	7176	16	Smiths Crinkle Chips Salt & Vinegar 330g	1	
14	2019-05-15	19	19272	16686	44	Thins Chips Light& Tangy 175g	1	
33	2019-05-18	45	45220	41651	22	Thins Chips Originl saltd 175g	1	

Count number of transactions by date

```
In [264]: transQuant = chips.groupby('DATE').sum()[['PROD_QTY', 'TOT_SALES']]
transQuant
# There's only 364 rows, meaning only 364 dates which indicates a missing date.
# Let's create a sequence of dates from 1 Jul 2018 to 30 Jun 2019 and use this to
# chart of number of transactions over time to find the missing date.
```

Out[264]:

	PROD_QTY	TOT_SALES
DATE		
2018-07-01	230	787.9
2018-07-02	250	905.6
2018-07-03	262	912.9
2018-07-04	227	758.2
2018-07-05	254	876.6
...
2019-06-26	241	860.3
2019-06-27	242	831.8
2019-06-28	307	1074.9
2019-06-29	264	933.3
2019-06-30	288	997.4

364 rows × 2 columns

```
In [265]: transCount = chips.groupby('DATE').count()['PROD_QTY']
transCount
```

Out[265]:

DATE	
2018-07-01	121
2018-07-02	129
2018-07-03	136
2018-07-04	119
2018-07-05	134
...	
2019-06-26	127
2019-06-27	127
2019-06-28	159
2019-06-29	139
2019-06-30	149

Name: PROD_QTY, Length: 364, dtype: int64

```
In [266]: trans_all = pd.merge(transQuant,transCount, on = 'DATE')
trans_all.rename(columns={'PROD_QTY_y': 'TRANS_COUNT'}, inplace=True)
trans_all
```

Out[266]:

	PROD_QTY_x	TOT_SALES	TRANS_COUNT
DATE			
2018-07-01	230	787.9	121
2018-07-02	250	905.6	129
2018-07-03	262	912.9	136
2018-07-04	227	758.2	119
2018-07-05	254	876.6	134
...
2019-06-26	241	860.3	127
2019-06-27	242	831.8	127
2019-06-28	307	1074.9	159
2019-06-29	264	933.3	139
2019-06-30	288	997.4	149

364 rows × 3 columns

Create a dataframe of all dates range from 2018-07-01 to 2019-06-30,

and then join it with the count of transactions by date


```
In [267]: alldates = pd.DataFrame(pd.date_range(start="2018-07-01",end="2019-06-30"), columns=['DATE'], index=alldates)
```

Out[267]:

	DATE
0	2018-07-01
1	2018-07-02
2	2018-07-03
3	2018-07-04
4	2018-07-05
...	...
360	2019-06-26
361	2019-06-27
362	2019-06-28
363	2019-06-29
364	2019-06-30

365 rows × 1 columns

```
In [268]: transdates = pd.merge(alldates, trans_all, on='DATE', how='left')
#transdates['PROD_QTY'] = transdates['PROD_QTY'].fillna(0)
transdates = transdates.fillna(0)
transdates
```

Out[268]:

	DATE	PROD_QTY_x	TOT_SALES	TRANS_COUNT
0	2018-07-01	230.0	787.9	121.0
1	2018-07-02	250.0	905.6	129.0
2	2018-07-03	262.0	912.9	136.0
3	2018-07-04	227.0	758.2	119.0
4	2018-07-05	254.0	876.6	134.0
...
360	2019-06-26	241.0	860.3	127.0
361	2019-06-27	242.0	831.8	127.0
362	2019-06-28	307.0	1074.9	159.0
363	2019-06-29	264.0	933.3	139.0
364	2019-06-30	288.0	997.4	149.0

365 rows × 4 columns

Identify the date that doesn't have any transactions

```
In [269]: zero = transdates.loc[transdates['TOT_SALES']==0]
zero
```

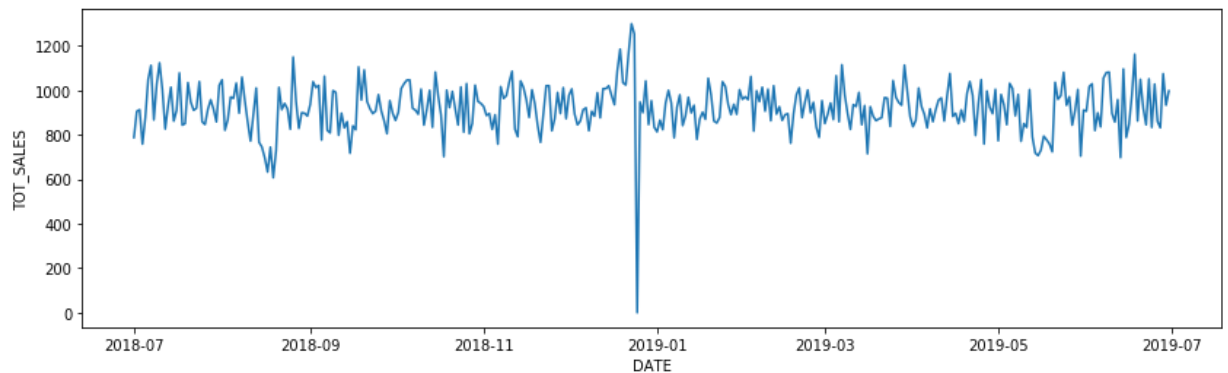
Out[269]:

	DATE	PROD_QTY_x	TOT_SALES	TRANS_COUNT
177	2018-12-25	0.0	0.0	0.0

```
In [270]: plt.figure(figsize=(14,4))

sns.lineplot(x='DATE',y='TOT_SALES',data=transdates)
```

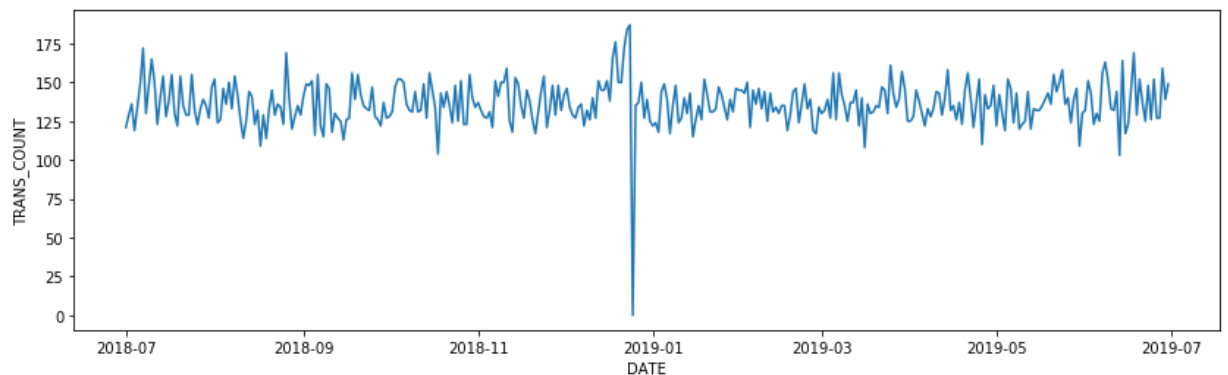
Out[270]: <matplotlib.axes._subplots.AxesSubplot at 0x13f65bbc3c8>



```
In [271]: plt.figure(figsize=(14,4))

sns.lineplot(x='DATE',y='TRANS_COUNT',data=transdates)
```

Out[271]: <matplotlib.axes._subplots.AxesSubplot at 0x13f4c72bb48>



```
In [272]: # We can see that the increase in sales occurs in the lead-up to Christmas and th
# there are zero sales on Christmas day itself. This is due to shops being closed
# Christmas day.
```

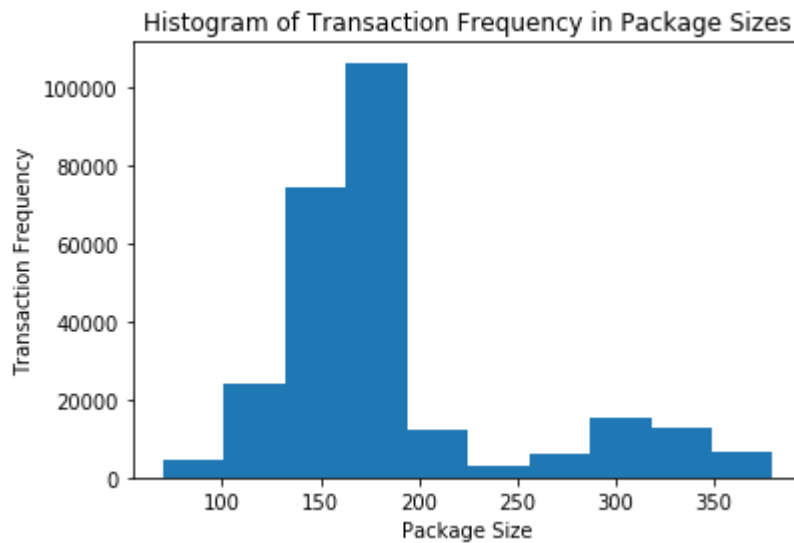
Create another feature - Package Size

```
In [273]: transaction_new['PACK_SIZE'] = transaction_new['PROD_NAME'].str.extract('(\d+)')
transaction_new['PACK_SIZE'] = transaction_new['PACK_SIZE'].astype(int)
```

```
In [274]: transaction_new['PACK_SIZE'].max()    # Maximum: 380
transaction_new['PACK_SIZE'].min()    # Minimum: 70
```

Out[274]: 70

```
In [275]: hist = plt.hist(transaction_new['PACK_SIZE'])
hist = plt.xlabel('Package Size')
hist = plt.ylabel('Transaction Frequency')
hist = plt.title('Histogram of Transaction Frequency in Package Sizes')
```



Create another feature - Brand

```
In [276]: brandlist = []
for b in transaction_new['PROD_NAME']:
    brand = b.split()[0]
    brandlist.append(brand.upper())
transaction_new['BRAND'] = brandlist
transaction_new.head(40)
```

29	2019-05-20	43	43110	39342	31	Infzns Crn Crnchers Tangy Gcamole 110g	1
30	2019-05-16	43	43147	39608	99	Pringles Sthrn FriedChicken 134g	1
31	2019-05-15	43	43227	40186	26	Pringles Sweet&Spcy BBQ 134g	4
32	2019-05-20	45	45127	41122	64	Red Rock Deli SR Salsa & Mzzrlla 150g	2
33	2019-05-18	45	45220	41651	22	Thins Chips Originl salted 175g	1
34	2018-08-16	51	51100	46802	48	Red Rock Deli Sp Salt & Truffle 150G	1

```
In [277]: transaction_new['BRAND'] = transaction_new['BRAND'].replace('RED', 'RDD')
transaction_new['BRAND'] = transaction_new['BRAND'].replace('SNBTS', 'SUNBITES')
transaction_new['BRAND'] = transaction_new['BRAND'].replace('INFZNS', 'INFUZIONI')
transaction_new['BRAND'] = transaction_new['BRAND'].replace('WW', 'WOOLWORTHS')
transaction_new['BRAND'] = transaction_new['BRAND'].replace('SMITH', 'SMITHS')
transaction_new['BRAND'] = transaction_new['BRAND'].replace('NCC', 'NATURAL')
transaction_new['BRAND'] = transaction_new['BRAND'].replace('DORITO', 'DORITOS')
transaction_new['BRAND'] = transaction_new['BRAND'].replace('GRAIN', 'GRNWVES')
```

In [278]:

transaction_new.head()

Out[278]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_
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	

In []:

In []:

Examine customer data

In [432]:

customer.groupby('LIFESTAGE').count().sort_values('LYLTY_CARD_NBR', ascending = F

Out[432]:

	LYLTY_CARD_NBR	PREMIUM_CUSTOMER
LIFESTAGE		
RETIREES	14805	14805
OLDER SINGLES/COUPLES	14609	14609
YOUNG SINGLES/COUPLES	14441	14441
OLDER FAMILIES	9780	9780
YOUNG FAMILIES	9178	9178
MIDAGE SINGLES/COUPLES	7275	7275
NEW FAMILIES	2549	2549

```
In [433]: customer.groupby('PREMIUM_CUSTOMER').count().sort_values('LYLTY_CARD_NBR', ascending=True)
```

Out[433]:

	LYLTY_CARD_NBR	LIFESTAGE
PREMIUM_CUSTOMER		
Mainstream	29245	29245
Budget	24470	24470
Premium	18922	18922

```
In [434]: all_data = pd.merge(customer, transaction_new, on='LYLTY_CARD_NBR', how='inner')
all_data
```

Out[434]:

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER	DATE	STORE_NBR	TXN_ID
0	1000	YOUNG SINGLES/COUPLES	Premium	2018-10-17	1	240378
1	1002	YOUNG SINGLES/COUPLES	Mainstream	2018-09-16	1	240394
2	1003	YOUNG FAMILIES	Budget	2019-03-07	1	240480
3	1003	YOUNG FAMILIES	Budget	2019-03-08	1	240481
4	1004	OLDER SINGLES/COUPLES	Mainstream	2018-11-02	1	241815
...
264829	2370701	YOUNG FAMILIES	Mainstream	2018-12-08	88	240378
264830	2370751	YOUNG FAMILIES	Premium	2018-10-01	88	240394
264831	2370961	OLDER FAMILIES	Budget	2018-10-24	88	240480
264832	2370961	OLDER FAMILIES	Budget	2018-10-27	88	240481
264833	2373711	YOUNG SINGLES/COUPLES	Mainstream	2018-12-14	88	241815

264834 rows × 13 columns



```
In [435]: Tot_by_customer = all_data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).sum()[['PROD_QTY', 'TOT_SALES']]
Tot_by_customer.head()
```

Out[435]:

		PROD_QTY	TOT_SALES
LIFESTAGE	PREMIUM_CUSTOMER		
OLDER FAMILIES	Budget	45065	168363.25
YOUNG SINGLES/COUPLES	Mainstream	38632	157621.60
RETIREES	Mainstream	40518	155677.05
YOUNG FAMILIES	Budget	37111	139345.85
OLDER SINGLES/COUPLES	Budget	35220	136769.80

```
In [436]: # Sales are coming mainly from Budget - older families,
#           Mainstream - young singles/couples,
#           and Mainstream - retirees
```

```
In [497]: Tot_by_Lifestage = all_data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).sum()[['TOT_SALES']]
Tot_by_Lifestage
```

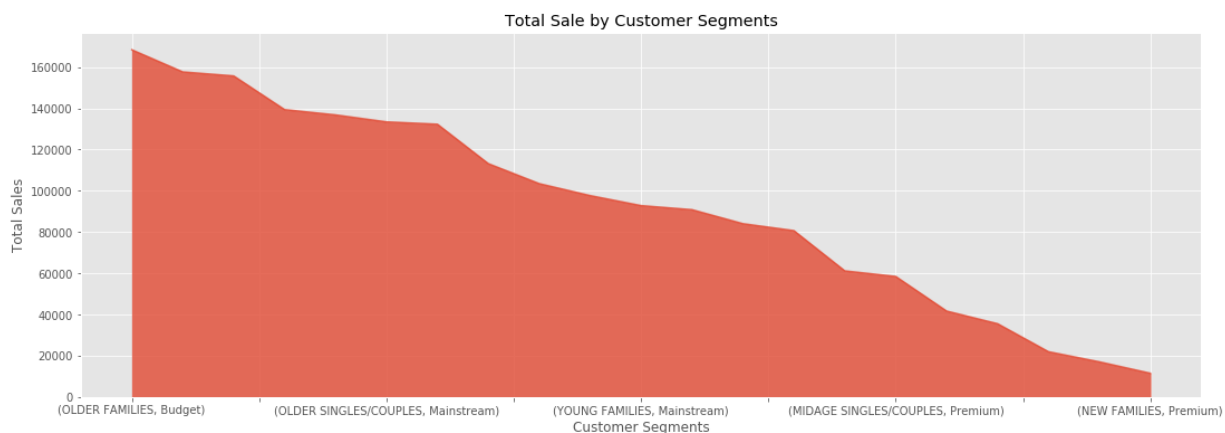
```
Out[497]: LIFESTAGE      PREMIUM_CUSTOMER      TOT_SALES
MIDAGE SINGLES/COUPLES Budget      35514.80
              Mainstream    90803.85
              Premium      58432.65
NEW FAMILIES      Budget      21928.45
              Mainstream    17013.90
              Premium      11491.10
OLDER FAMILIES      Budget    168363.25
              Mainstream   103445.55
              Premium      80658.40
OLDER SINGLES/COUPLES Budget    136769.80
              Mainstream   133393.80
              Premium     132263.15
RETIREES      Budget    113147.80
              Mainstream   155677.05
              Premium      97646.05
YOUNG FAMILIES      Budget    139345.85
              Mainstream    92788.75
              Premium      84025.50
YOUNG SINGLES/COUPLES Budget    61141.60
              Mainstream   157621.60
              Premium      41642.10
Name: TOT_SALES, dtype: float64
```



```
In [438]: plt.style.use('ggplot')
plt.figure(figsize=(18,6))

Tot = Tot_by_customer['TOT_SALES'].plot.area(alpha=0.8)

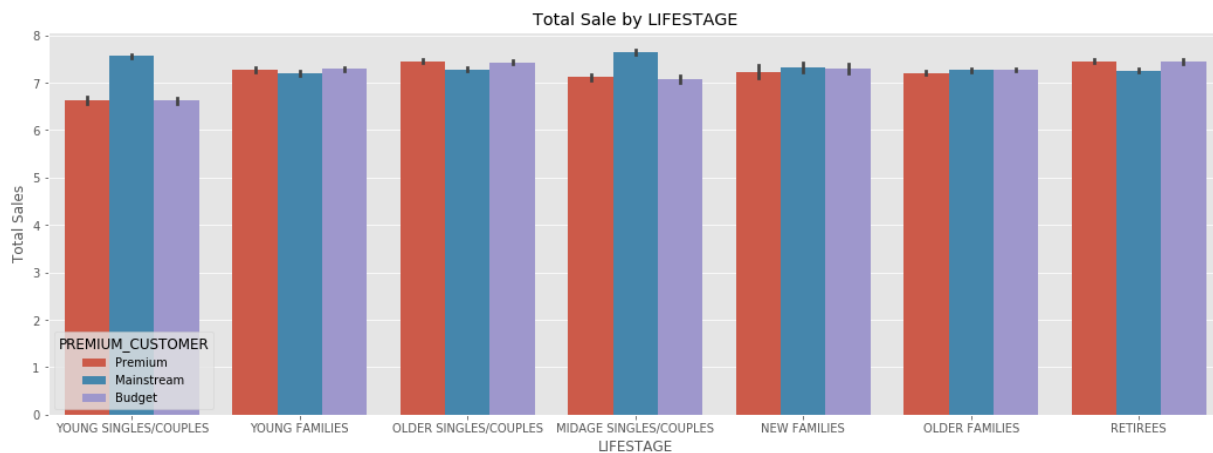
Tot = plt.xlabel('Customer Segments')
Tot = plt.ylabel('Total Sales')
Tot = plt.title('Total Sale by Customer Segments')
```



```
In [439]: plt.figure(figsize=(18,6))
tot_lifestage = sns.barplot(x='LIFESTAGE',y='TOT_SALES', hue = 'PREMIUM_CUSTOMER')

tot_lifestage.set_xlabel('LIFESTAGE')
tot_lifestage.set_ylabel('Total Sales')
tot_lifestage.set_title('Total Sale by LIFESTAGE')
```

Out[439]: Text(0.5, 1.0, 'Total Sale by LIFESTAGE')



```
In [441]: all_data['AVG_UNIT'] = all_data['PROD_QTY']/all_data['LYLTY_CARD_NBR']
```

```
In [442]: sum_qt = all_data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).sum()['PROD_QTY']
```

```
In [443]: nunique = all_data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).nunique()['LYLTY_CARD_NBR']
```

```
In [452]: combine = pd.merge(sum_qt, nunique, on=(['LIFESTAGE', 'PREMIUM_CUSTOMER']))
combine['AVG_UNIT'] = combine['PROD_QTY']/combine['LYLTY_CARD_NBR']
combine.reset_index(inplace=True)
combine.head()
```

Out[452]:

	LIFESTAGE	PREMIUM_CUSTOMER	PROD_QTY	LYLTY_CARD_NBR	AVG_UNIT
0	MIDAGE SINGLES/COUPLES	Budget	9496	1504	6.313830
1	MIDAGE SINGLES/COUPLES	Mainstream	22699	3340	6.796108
2	MIDAGE SINGLES/COUPLES	Premium	15526	2431	6.386672
3	NEW FAMILIES	Budget	5571	1112	5.009892
4	NEW FAMILIES	Mainstream	4319	849	5.087161

```
In [451]: plt.figure(figsize=(14,6))
sns.barplot(x='LIFESTAGE', y='AVG_UNIT', hue='PREMIUM_CUSTOMER', data=combine)
```

Out[451]: <matplotlib.axes._subplots.AxesSubplot at 0x13f5f85d508>



```
In [453]: Avg_Price_per_Unit = Tot_by_customer['TOT_SALES']/Tot_by_customer['PROD_QTY']
Avg_Price_per_Unit.sort_values(ascending = False)
```

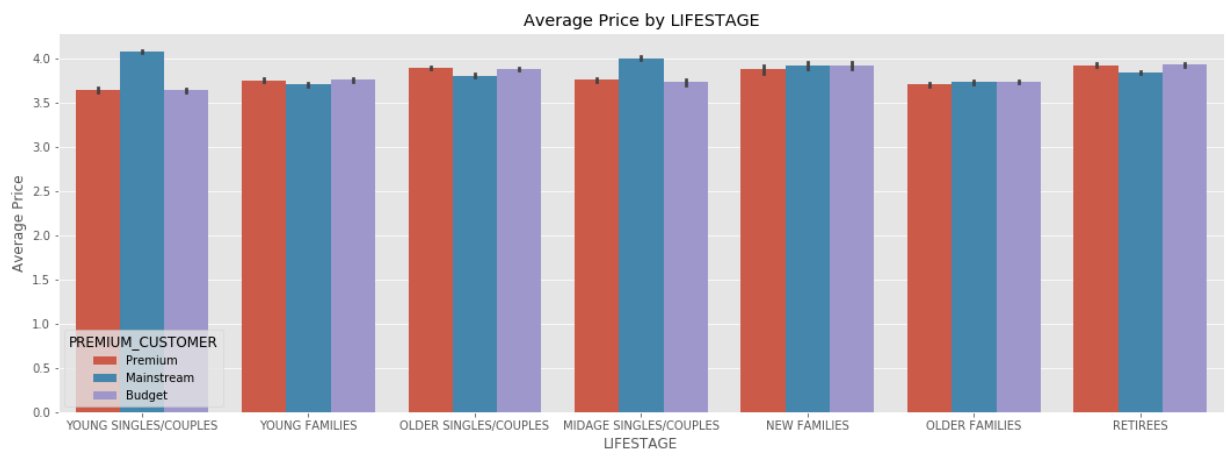
```
Out[453]: LIFESTAGE      PREMIUM_CUSTOMER
YOUNG SINGLES/COUPLES  Mainstream      4.080079
MIDAGE SINGLES/COUPLES Mainstream      4.000346
NEW FAMILIES          Mainstream      3.939315
                     Budget          3.936178
RETIREES              Budget          3.933660
                     Premium          3.924050
OLDER SINGLES/COUPLES Premium          3.891695
NEW FAMILIES          Premium          3.886067
OLDER SINGLES/COUPLES Budget          3.883299
RETIREES              Mainstream      3.842170
OLDER SINGLES/COUPLES Mainstream      3.811578
MIDAGE SINGLES/COUPLES Premium          3.763535
YOUNG FAMILIES        Budget          3.754840
                     Premium          3.750134
MIDAGE SINGLES/COUPLES Budget          3.739975
OLDER FAMILIES        Budget          3.736009
                     Mainstream      3.726962
YOUNG FAMILIES        Mainstream      3.705029
OLDER FAMILIES        Premium          3.704855
YOUNG SINGLES/COUPLES Premium          3.675060
                     Budget          3.667542

dtype: float64
```

```
In [454]: plt.figure(figsize=(18,6))
avgPrice_lifestage = sns.barplot(x='LIFESTAGE', y = all_data['TOT_SALES']/all_data['PROD_QTY'])

avgPrice_lifestage .set_xlabel('LIFESTAGE')
avgPrice_lifestage .set_ylabel('Average Price')
avgPrice_lifestage .set_title('Average Price by LIFESTAGE')
```

```
Out[454]: Text(0.5, 1.0, 'Average Price by LIFESTAGE')
```



```
In [455]: main = [Avg_Price_per_Unit['YOUNG SINGLES/COUPLES']['Mainstream'],Avg_Price_per_Unit['YOUNG SINGLES/COUPLES']['Mainstream']]
others = [Avg_Price_per_Unit['YOUNG SINGLES/COUPLES']['Budget'],Avg_Price_per_Unit['YOUNG SINGLES/COUPLES']['Mainstream']]
```

```
In [456]: ttest_ind(main, others)
```

```
Out[456]: Ttest_indResult(statistic=7.6068869237118735, pvalue=0.0016027797701074072)
```

```
In [473]: # The t-test results in a p-value of 0.0016,  
# the unit price for mainstream, young and mid-age singles and couples are signif  
# that of budget or premium, young and midage singles and couples.
```

Implementing Apriori algorithm

```
In [518]: #from apyori import apriori  
#from mlxtend.frequent_patterns import apriori  
#from mlxtend.frequent_patterns import association_rules
```

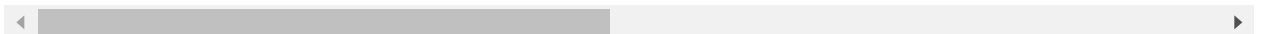
Uncover associations in Brand

```
In [522]: df = all_data
df_young_main = df[(df['LIFESTAGE']=='YOUNG SINGLES/COUPLES') & (df['PREMIUM_CUSTOMER']=='Mainstream')]
df_young_main
```

Out[522]:

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER	DATE	STORE_NBR	TXN_ID
1	1002	YOUNG SINGLES/COUPLES	Mainstream	2018-09-16	1	1002
9	1010	YOUNG SINGLES/COUPLES	Mainstream	2018-09-09	1	1010
10	1010	YOUNG SINGLES/COUPLES	Mainstream	2018-12-14	1	1010
21	1018	YOUNG SINGLES/COUPLES	Mainstream	2018-09-03	1	2101
22	1018	YOUNG SINGLES/COUPLES	Mainstream	2018-11-28	1	2201
...
264785	272391	YOUNG SINGLES/COUPLES	Mainstream	2018-12-07	272	270201
264805	2330041	YOUNG SINGLES/COUPLES	Mainstream	2018-09-23	77	236718
264818	2330321	YOUNG SINGLES/COUPLES	Mainstream	2018-07-30	77	236756
264824	2370181	YOUNG SINGLES/COUPLES	Mainstream	2018-08-02	88	240146
264833	2373711	YOUNG SINGLES/COUPLES	Mainstream	2018-12-14	88	241811

20854 rows × 14 columns



```
In [523]: basket1 = df_young_main.pivot_table('PROD_QTY', ['LYLTY_CARD_NBR'], 'BRAND').fillna(0)
```

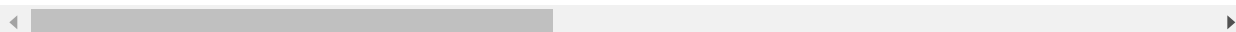
```
In [524]: def encode_units(x):
            if x <= 0:
                return 0
            if x >= 1:
                return 1

basket_sets_1 = basket1.applymap(encode_units)
basket_sets_1
```

Out[524]:

	BRAND	BURGER	CCS	CHEETOS	CHEEZELS	COBS	DORITOS	FRENCH	GRNWVES
LYLTY_CARD_NBR									
1002	0	0	0	0	0	0	0	0	0
1010	0	0	0	0	0	0	1	0	0
1018	0	0	0	0	0	0	0	0	0
1020	0	0	0	0	0	0	0	0	1
1060	0	0	0	0	0	0	1	0	0
...
272391	0	0	0	0	0	0	0	0	0
2330041	0	0	0	0	0	0	0	0	1
2330321	0	0	0	0	0	0	0	0	0
2370181	0	0	0	0	0	0	0	0	0
2373711	0	0	0	0	0	0	0	0	0

8088 rows × 23 columns



```
In [525]: frequent_itemsets_young = apriori(basket_sets_1, min_support=0.07, use_colnames=True)
frequent_itemsets_young.sort_values('support', ascending = False).head()
```

Out[525]:

	support	itemsets
4	0.378956	(KETTLE)
1	0.267928	(DORITOS)
6	0.250742	(PRINGLES)
8	0.203759	(SMITHS)
3	0.140084	(INFUZIONI)

```
In [492]: # The 'YOUNG SINGLES/COUPLES' & 'Mainstream' segment tend to favor the following
# - Kettle
# - Doritos
# - Pringles
# - Smiths
# - INFUZIONI
```

```
In [554]: #rules_young = association_rules(frequent_itemsets_young, metric="lift", min_thre
#rules_young.head())
```

Out[554]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	
0	(Smiths)	(Doritos)	0.193744	0.238872	0.047725	0.246331	1.031222	0.001445	
1	(Doritos)	(Smiths)	0.238872	0.193744	0.047725	0.199793	1.031222	0.001445	

```
In [543]: '''
Explanation of the output:

The output shows the support and confidence values for (B, A) and (A, B) as well.

A high lift value which means that it occurs more frequently than would be expect
'''
```

Uncover associations in Package Size

```
In [493]: basket_2 = df_young_main.pivot_table('PROD_QTY', ['LYLTY_CARD_NBR'], 'PACK_SIZE').f
```

```
In [494]: def encode_units(x):
            if x <= 0:
                return 0
            if x >= 1:
                return 1

basket_sets_2 = basket_2.applymap(encode_units)
basket_sets_2
```

Out[494]:

	PACK_SIZE	70	90	110	125	134	135	150	160	165	170	...	180	190	200	210	220
LYLTY_CARD_NBR																	
	1002	0	0	0	0	0	0	1	0	0	0	...	0	0	0	0	0
	1010	0	0	0	0	0	0	0	0	0	1	...	0	0	0	0	0
	1018	1	0	0	0	0	0	1	0	1	0	...	0	0	0	0	0
	1020	0	0	0	0	0	0	1	0	0	0	...	1	0	0	0	0
	1060	0	0	0	0	0	0	0	0	1	1	...	0	0	0	0	0

	272391	0	0	0	0	0	1	0	0	0	0	...	0	0	0	0	0
	2330041	0	0	0	0	0	0	0	0	0	0	...	0	0	0	1	0
	2330321	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
	2370181	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

8088 rows × 21 columns

```
In [496]: frequent_itemsets_2 = apriori(basket_sets_2, min_support=0.07, use_colnames=True)
frequent_itemsets_2.sort_values('support', ascending = False).head()
```

Out[496]:

	support	itemsets
5	0.448566	(175)
2	0.318867	(150)
1	0.250742	(134)
0	0.219708	(110)
4	0.173096	(170)


```
In [ ]: # The 'YOUNG SINGLES/COUPLES' & 'Mainstream' segment tend to favor the following  
# - 175g  
# - 150g  
# - 134g
```

Conclusion

Sales have mainly generated through :

Budget - older families, Mainstream - young singles/couples, and Mainstream retirees shoppers.

We found a trends of :

- High spend in chips for mainstream young singles/couples and retirees, due to there being more of them than other buyers

- Mainstream, midage and young singles and couples are more likely to pay more per packet of chips

- The Mainstream young singles and couples are 38% more likely to purchase Kettle chips compared to the rest of the population

(The Category Manager may want to increase the category's performance by off-locating some Kettle and smaller packs of chips

in discretionary space near segments where young singles and couples frequent more often to increase visibility and impulse behaviour.)

In []: