# Here is the background information on your task

You are part of retail analytics team and have been approached by your client, the Category Manager for Chips, who wants to better understand the types of customers who purchase Chips and their purchasing behaviour within the region.

Remember, our end goal is to form a strategy based on the findings to provide a clear recommendation to Julia the Category Manager so make sure your insights can have a commercial application.

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        import re
        import warnings
        warnings.filterwarnings("ignore")
In [2]: customers = pd.read_csv('.\\data\\QVI_purchase_behaviour.csv')
        customers.head()
Out[2]:
                                          LIFESTAGE PREMIUM CUSTOMER
           LYLTY_CARD_NBR
        0
                      1000
                            YOUNG SINGLES/COUPLES
                                                                Premium
                       1002 YOUNG SINGLES/COUPLES
                                                              Mainstream
        1
        2
                      1003
                                    YOUNG FAMILIES
                                                                  Budget
                                                              Mainstream
        3
                      1004
                             OLDER SINGLES/COUPLES
        4
                      1005 MIDAGE SINGLES/COUPLES
                                                              Mainstream
In [3]: transaction = pd.read_excel('.\\data\\QVI_transaction_data.xlsx')
```

transaction.head()

Out[3]:		DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY
	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
		1				_		

## I don't like the title letters in the column names and the date as a number

```
In [4]: customers.columns = customers.columns.str.lower()
    transaction.columns = transaction.columns.str.lower()

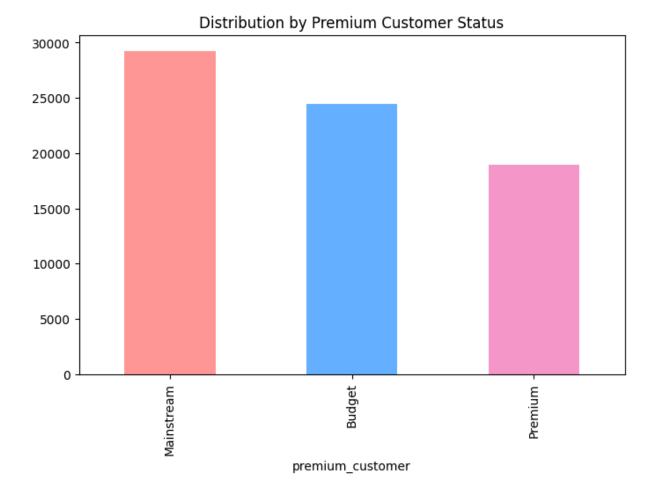
In [5]: start_date = pd.to_datetime('1899-12-30')
    transaction['date'] = transaction['date'].apply(lambda x: start_date + pd.Timedelta
In [6]: customers.info(), transaction.info()
```

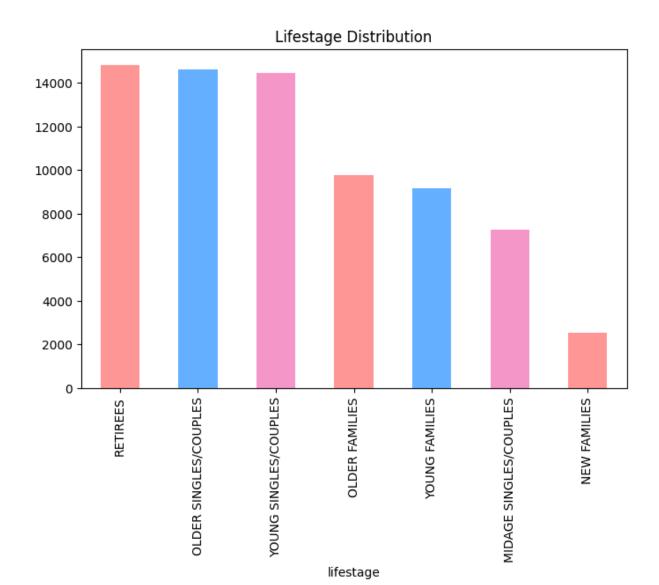
```
<class 'pandas.core.frame.DataFrame'>
       RangeIndex: 72637 entries, 0 to 72636
       Data columns (total 3 columns):
        # Column Non-Null Count Dtype
       --- -----
                            -----
        0 lylty_card_nbr 72637 non-null int64
        1 lifestage 72637 non-null object
            premium_customer 72637 non-null object
       dtypes: int64(1), object(2)
       memory usage: 1.7+ MB
       <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 datetime64[ns]
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: datetime64[ns](1), float64(1), int64(5), object(1)
       memory usage: 16.2+ MB
Out[6]: (None, None)
```

#### I want to see the distribution in the database with customers

```
In [7]: # Plot distribution by Premium Customer Status
   plt.figure(figsize=(8, 5))
        customers.premium_customer.value_counts().plot(kind='bar', color=['#FF9999', '#66B3
        plt.title('Distribution by Premium Customer Status')
        plt.show()

# Plot Lifestage Distribution
        plt.figure(figsize=(8, 5))
        customers.lifestage.value_counts().plot(kind='bar', color=['#FF9999', '#66B3FF', '#
        plt.title('Lifestage Distribution')
        plt.show()
```





## Let's look at the duplicates

```
In [8]: transaction.duplicated().sum()
Out[8]: np.int64(1)
In [9]: transaction.drop_duplicates(inplace=True)
    transaction.duplicated().sum()
Out[9]: np.int64(0)
```

# Add columns with customer types to the table with transactions

```
In [10]: df = pd.merge(transaction, customers, on='lylty_card_nbr')
    df.head()
```

Out[10]:		date	store_nbr	lylty_card_nbr	txn_id	prod_nbr	prod_name	prod_qty	tot_sales
	0	2018- 10-17	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0
	1	2019- 05-14	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3
	2	2019- 05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9
	3	2018- 08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	15.0
	4	2018- 08-18	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	13.8
In [11]:	df	.shape,	, transacti	ion.shape, cus	tomers.	shape			
Out[11]:	((	264835	, 10), (26	4835, 8), (726	37, 3))				
	W	e only	need chi	ps					
In [12]:		_	-			•	rts in product n (r'\b(Chips?)\b		\b \b(red)
	A	dd a fe	ew necess	ary columns	such a	s brand a	nd weight		
In [13]:	ch	ips_pro	oducts['bra	and'] = chips_	product	s['prod_na	ame'].str.split(	).str[0]	
In [14]:	ch	ips_pro	oducts['we	ight'] = chips	_produc	ts['prod_r	name'].str[-4:]		

In [15]: chips\_products[['prod\_qty', 'tot\_sales']].describe()

Out[15]:		prod_qty	tot_sales	
	count	101986.000000	101986.000000	
	mean	1.907154	6.738020	
	std	0.943519	3.733085	
	min	1.000000	1.700000	
	25%	2.000000	5.400000	
	50%	2.000000	6.600000	
	75%	2.000000	7.800000	
	max	200.000000	650.000000	

# I see an outlier in the data, let's take a closer look

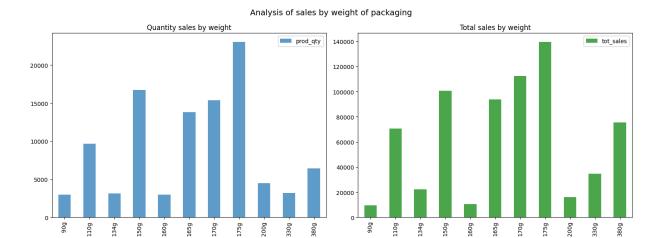
In [16]:	<pre>chips_products[chips_products['prod_qty'] == 200]</pre>										
Out[16]:		date	store_nbr	lylty_card_nbr	txn_id	prod_nbr	prod_name	prod_qty	tot_sales		
	69762	2018- 08-19	226	226000	226201	4	Dorito Corn Chp Supreme 380g	200	650.0		
	69763	2019- 05-20	226	226000	226210	4	Dorito Corn Chp Supreme 380g	200	650.0		
	4				_				•		
In [17]:	chips_p	oroduct	s = chips_	products[chips	s_produc	ts['lylty_	_card_nbr']	!= 226000]			
In [18]:	chips_p	oroduct	s[['prod_d	ty', 'tot_sale	es']].de	scribe()					

```
Out[18]:
                      prod_qty
                                      tot_sales
          count 101984.000000 101984.000000
                       1.903269
                                      6.725405
          mean
            std
                       0.347382
                                      2.412724
                       1.000000
                                      1.700000
            min
           25%
                       2.000000
                                      5.400000
            50%
                       2.000000
                                      6.600000
           75%
                       2.000000
                                      7.800000
                       5.000000
            max
                                     29.500000
```

### Many identical brands are recorded differently let's combine them

Out[25]:		date	store_nbr	lylty_card_nbr	txn_id	prod_nbr	prod_name	prod_qty	tot_sales
	0	2018- 10-17	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0
	2	2019- 05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9
	3	2018- 08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	15.0
	6	2019- 05-16	4	4149	3333	16	Smiths Crinkle Chips Salt & Vinegar 330g	1	5.7
	8	2018- 08-20	5	5026	4525	42	Doritos Corn Chip Mexican Jalapeno 150g	1	3.9
	•								•

## What volume of packaging is sold more?



# How many brands produce their products in each weight?

In [27]: chips\_products.groupby('weight').agg({'brand': 'nunique'}).sort\_values('brand', asc

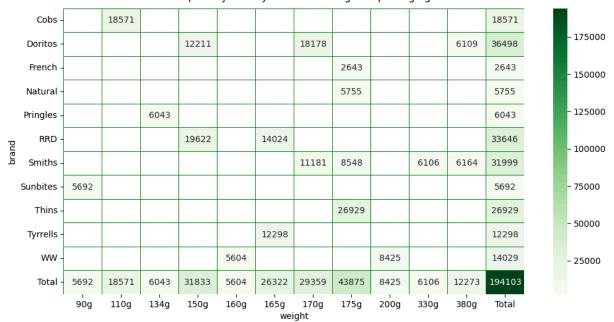
Out[27]: brand

	brand
weight	
175g	4
150g	2
170g	2
380g	2
165g	2
90g	1
110g	1
134g	1
160g	1
200g	1
330g	1

```
In [28]: chips_products.groupby('weight')['brand'].unique()
```

```
Out[28]: weight
           90g
                                        [Sunbites]
          110g
                                            [Cobs]
          134g
                                        [Pringles]
                                    [Doritos, RRD]
          150g
          160g
                                               [WW]
                                   [Tyrrells, RRD]
          165g
          170g
                                 [Smiths, Doritos]
                  [Natural, Smiths, Thins, French]
          175g
          200g
                                               [WW]
          330g
                                           [Smiths]
          380g
                                 [Doritos, Smiths]
          Name: brand, dtype: object
In [29]:
         chips_products.groupby('weight')['prod_qty'].agg(['mean', 'sum']).sort_values('sum'
Out[29]:
                    mean
                            sum
          weight
           175g 1.902645 43875
           150g
                1.900705 31833
           170q 1.904821
                          29359
           165q 1.900643 26322
           110g 1.915919 18571
           380g
                1.912874 12273
           200q 1.883523
                            8425
           330g 1.909916
                            6106
           134g 1.914159
                            6043
            90g
                1.892287
                            5692
           160g 1.886869
                            5604
In [30]: pivot_brand_weight = chips_products.pivot_table(
             index='brand',
             columns='weight',
             values='prod_qty',
             aggfunc='sum',
             margins=True,
             margins_name='Total'
         plt.figure(figsize=(12, 6))
         plt.title('Total quantity sold by brand and weight of packaging',pad=10)
         sns.heatmap(pivot_brand_weight, annot=True, fmt='.0f', cmap='Greens', linewidths=0.
```

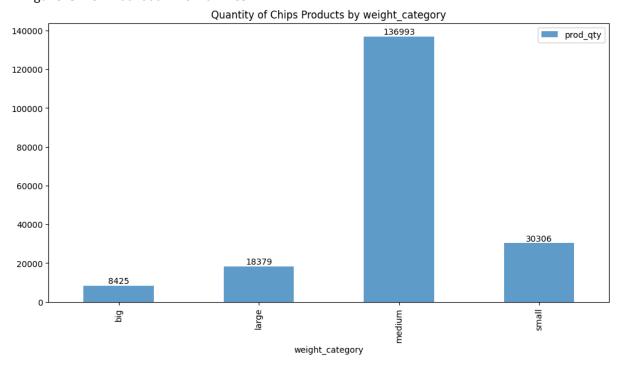
#### Total quantity sold by brand and weight of packaging



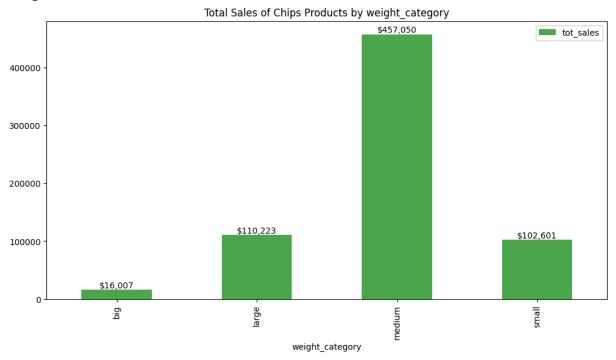
### Let's make a column with a weight category.

```
In [31]: conditions = [
             chips_products['weight'].isin([' 90g', '110g', '134g']),
             chips_products['weight'].isin(['150g', '160g', '165g', '175g', '170g']),
             chips_products['weight'].isin(['200g']),
             chips_products['weight'].isin(['330g', '380g'])
         ]
         choices = ['small', 'medium', 'big', 'large']
         chips_products['weight_category'] = np.select(conditions, choices, default='unknown')
         chips_products.groupby('weight_category')['weight'].unique()
Out[31]: weight_category
                                            [200g]
         big
                                      [330g, 380g]
          large
                    [175g, 170g, 150g, 165g, 160g]
         medium
                                [110g, 134g, 90g]
          small
         Name: weight, dtype: object
In [32]: plt.figure(figsize=(12, 6))
         ax = chips_products.groupby(['weight_category']).agg({'prod_qty':'sum'}).sort_index
         plt.title('Quantity of Chips Products by weight_category')
         # Add values over columns
         for i, v in enumerate(chips_products.groupby(['weight_category']).agg({'prod_qty':'
             ax.text(i, v, str(int(v)), ha='center', va='bottom')
         plt.show()
```

<Figure size 1200x600 with 0 Axes>



<Figure size 1200x600 with 0 Axes>



```
Out[33]: brand
```

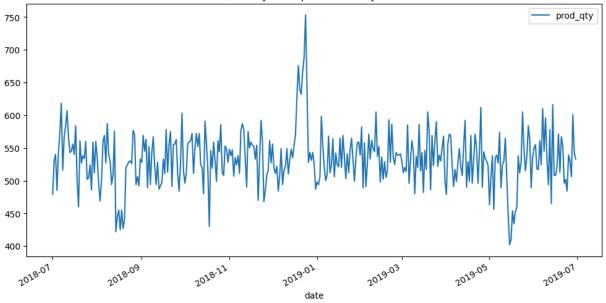
#### weight\_category

```
medium 8
small 3
large 2
big 1
```

```
In [34]: pivot_brand_weight_qty= chips_products.pivot_table(
             index='brand',
             columns='weight',
             values='prod_qty',
             aggfunc='sum'
         perc_pivot_brand_weight_qty = pivot_brand_weight_qty.div(pivot_brand_weight_qty.sum
         perc_pivot_brand_weight_qty.sum(axis=0).sort_values(ascending=False)
Out[34]: weight
         175g
                 22.603978
                 16.400056
          150g
                 15.125475
          170g
          165g
                13.560841
          110g
                 9.567601
                  6.322932
          380g
          200g
                  4.340479
          330g
                  3.145753
          134g
                  3.113296
          90g
                   2.932464
          160g
                   2.887127
         dtype: float64
In [35]: pivot_brand_weight_sale= chips_products.pivot_table(
             index='brand',
             columns='weight',
             values='tot_sales',
             aggfunc='sum'
         perc_pivot_brand_weight_sale = pivot_brand_weight_sale.div(pivot_brand_weight_sale.
         perc_pivot_brand_weight_sale.sum(axis=0).sort_values(ascending=False)
```

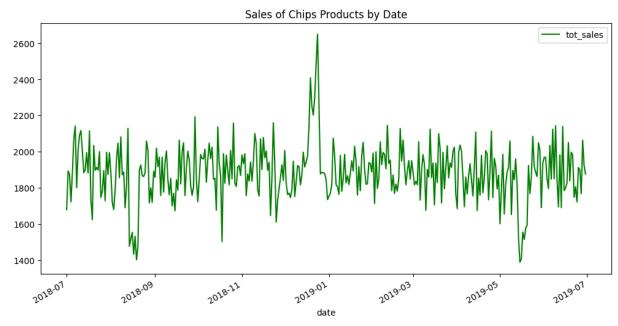
```
Out[35]: weight
        175g
                20.366499
        170g
                16.387093
        150g 14.666758
        165g 13.664037
        380g 10.995975
        110g 10.288887
        330g
               5.074359
                3.259357
        134g
        200g
                2.333850
        160g
                1.552391
         90g
                1.410793
        dtype: float64
```

## Let's look at the dynamics of sales over time.



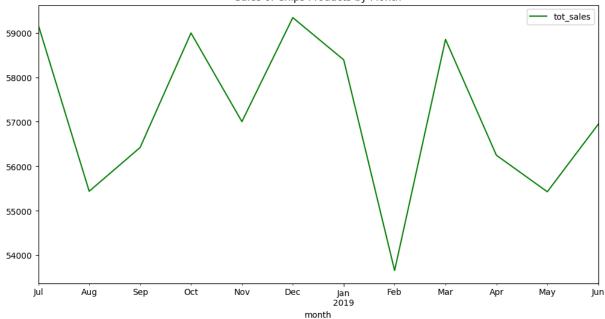
In [38]: chips\_products.groupby(['date']).agg({'tot\_sales':'sum'}).sort\_index().plot(figsize

Out[38]: <Axes: title={'center': 'Sales of Chips Products by Date'}, xlabel='date'>



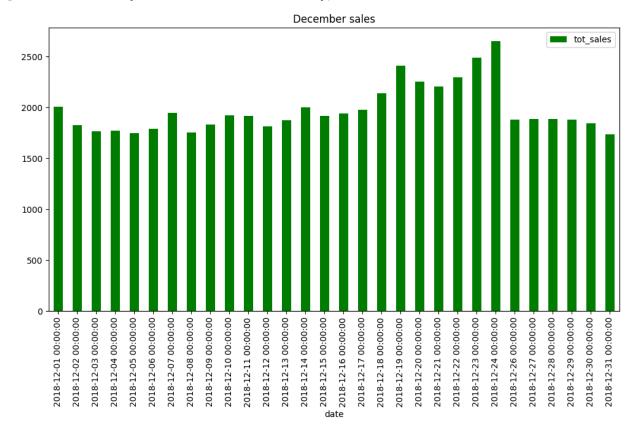
In [39]: chips\_products['month'] = chips\_products['date'].dt.to\_period('M')
In [40]: chips\_products.groupby(['month']).agg({'tot\_sales':'sum'}).sort\_index().plot(figsiz)

#### Sales of Chips Products by Month



```
In [41]: december_sales = chips_products[chips_products['month'] == '2018-12'].groupby(['dat
december_sales.plot(figsize=(12, 6), kind='bar', x='date', y='tot_sales', color='gr
```

Out[41]: <Axes: title={'center': 'December sales'}, xlabel='date'>



We have a gap in the data for 2018-12-25 and then a suspicious decline in sales from the 26th.

```
In [42]: december_sales.groupby(['date']).agg({'tot_sales':'sum'}).sort_index()
```

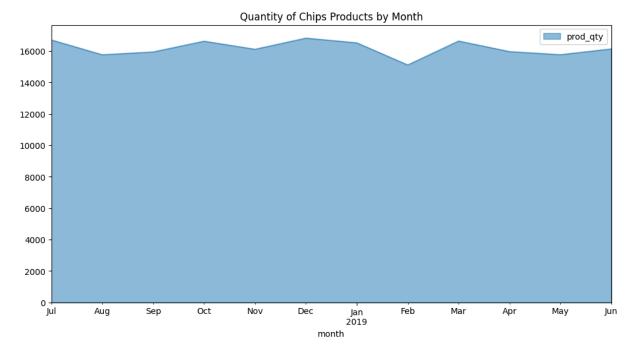
date	
2018-12-01	2006.3
2018-12-02	1827.2
2018-12-03	1762.8
2018-12-04	1770.6
2018-12-05	1746.7
2018-12-06	1789.8
2018-12-07	1947.3
2018-12-08	1751.9
2018-12-09	1833.9
2018-12-10	1923.2
2018-12-11	1916.9
2018-12-12	1816.1
2018-12-13	1871.0
2018-12-14	1997.4
2018-12-15	1915.6
2018-12-16	1942.8
2018-12-17	1977.9
2018-12-18	2140.6
2018-12-19	2409.0
2018-12-20	2252.6
2018-12-21	2202.0
2018-12-22	2298.1
2018-12-23	2487.1
2018-12-24	2649.0
2018-12-26	1877.2
2018-12-27	1884.8
2018-12-28	1884.0
2018-12-29	1877.9
2018-12-30	1846.5

date

**2018-12-31** 1734.4

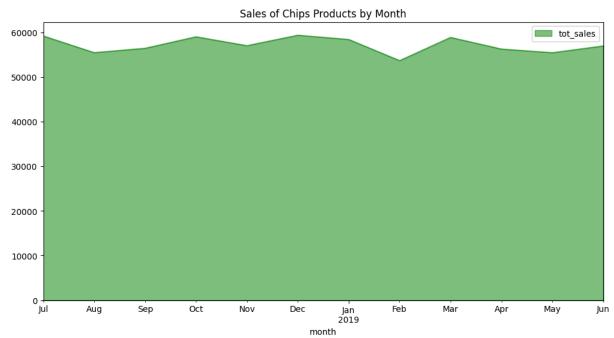
In [43]: chips\_products.groupby(['month']).agg({'prod\_qty':'sum'}).sort\_index().plot(figsize

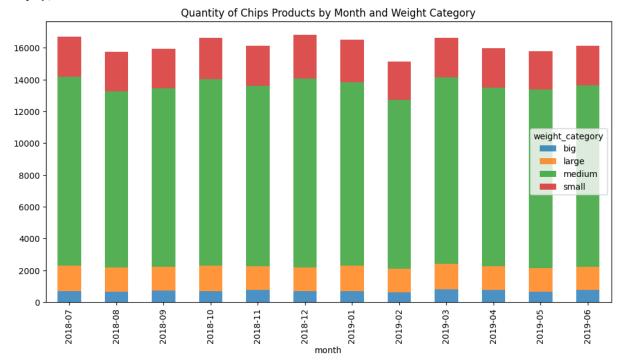
Out[43]: <Axes: title={'center': 'Quantity of Chips Products by Month'}, xlabel='month'>



In [44]: chips\_products.groupby(['month']).agg({'tot\_sales':'sum'}).sort\_index().plot(figsiz

Out[44]: <Axes: title={'center': 'Sales of Chips Products by Month'}, xlabel='month'>





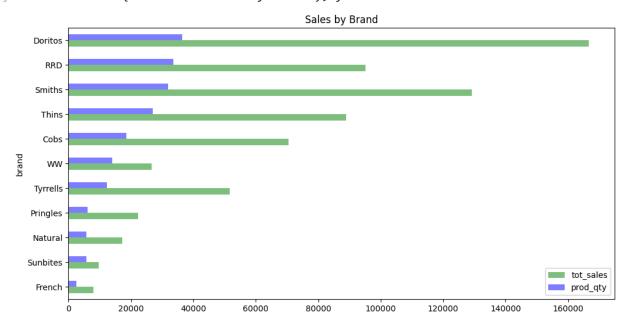
#### Let's see how each brand is sold.

```
In [46]: chips_products.groupby(['brand']).agg({'tot_sales':['sum','mean'], 'prod_qty':['sum', 'sum'), ascending=False)
```

		tot_sales		prod_qty
	sum	mean	sum	mean
brand				
Doritos	166649.3	8.744781	36498	1.915202
Smiths	129237.8	7.659898	31999	1.896574
RRD	95046.0	5.345970	33646	1.892457
Thins	88852.5	6.312789	26929	1.913250
Cobs	70569.8	7.280491	18571	1.915919
Tyrrells	51647.4	8.017293	12298	1.909034
ww	26655.1	3.581231	14029	1.884858
Pringles	22355.4	7.081216	6043	1.914159
Natural	17265.0	5.679276	5755	1.893092
Sunbites	9676.4	3.216888	5692	1.892287
French	7929.0	5.591678	2643	1.863893

Out[46]:

Out[47]: <Axes: title={'center': 'Sales by Brand'}, ylabel='brand'>



## Who is buying more chips?

```
In [48]: # sales by lifestage category
    chips_products.groupby(['lifestage']).agg(
```

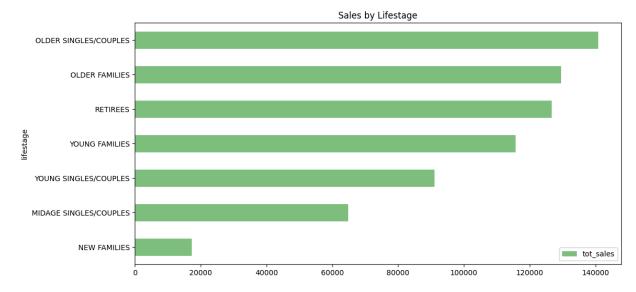
```
total_sales=('tot_sales', 'sum'),
  average_sales =('tot_sales', 'mean'),
  total_qty=('prod_qty', 'sum'),
  average_qty=('prod_qty', 'mean'),
  count_sales=('tot_sales', 'count')).sort_values(by='count_sales', ascending=Fal
```

### Out[48]: total\_sales average\_sales total\_qty average\_qty count\_sales

#### lifestage

OLDER SINGLES/COUPLES	140775.55	6.815898	39481	1.911543	20654
OLDER FAMILIES	129463.70	6.694436	37657	1.947205	19339
RETIREES	126699.10	6.772094	35295	1.886525	18709
YOUNG FAMILIES	115676.20	6.695774	33543	1.941595	17276
YOUNG SINGLES/COUPLES	91033.50	6.588514	25158	1.820800	13817
MIDAGE SINGLES/COUPLES	64854.00	6.759145	18176	1.894320	9595
NEW FAMILIES	17381.65	6.700713	4793	1.847726	2594

Out[49]: <Axes: title={'center': 'Sales by Lifestage'}, ylabel='lifestage'>



```
unique_clients_by_lifestage['sum_by_clients'] = unique_clients_by_lifestage['total_
unique_clients_by_lifestage
```

Out[50]:		lifesta	age	cnt_clie	ents	total_s	ales	mean_	sales	coun	t_sales	cou	nt_by_	clients	sun
	0	MIDA SINGLES/COUP		4	977	6485	4.00	6.75	9145		9595		1.9	927868	
	1	NEW FAMIL	LIES	1	642	1738	1.65	6.70	0713		2594		1.5	79781	
	2	OLDER FAMIL	LIES	7	473	12946	3.70	6.69	94436		19339		2.5	87850	
	3	OLI SINGLES/COUP	DER	10	538	14077	5.55	6.81	5898		20654		1.9	959954	
	4	RETIR	EES	10	259	12669	9.10	6.77	'2094		18709 1.8		1.8	.823667	
	5	YOUNG FAMIL	LIES	6	963	11567	6.20	6.69	5774		17276		2.4	181114	
	6	YOU SINGLES/COUP		8	718	9103	3.50	6.58	88514		13817		1.5	584882	
	•														<b>D</b>
In [51]:	) pl	<pre>pivot_brand_weight = chips_products.pivot_table(     index='lifestage',     columns='weight',     values='tot_sales',     aggfunc='sum' ) plt.figure(figsize=(12, 6)) plt.title('Total quantity sold by brand and weight of packaging',pad=10) sns.heatmap(pivot_brand_weight, annot=True, fmt='.0f', cmap='Greens', linewidths=0.</pre>													
					Total	quantity	sold by	brand an	d weigh	t of pack	kaging				
	MID	AGE SINGLES/COUPLES -	799	6996	2087	9387	1026	8812	10627	12992	1385	3352	7393		
		NEW FAMILIES -	177	2060	655	2459	234	2354	2822	3406	359	758	2098		25000
		OLDER FAMILIES -	2050	12027	4037	20042	2345	18294	20694	26913	3665	6549	12848		20000
lifectade	OLI	DER SINGLES/COUPLES -	1889	14812	4729	20264	2107	18578	23218	28873	3135	7182	15988	-	15000
		RETIREES -	1703	13688	4299	18205	1693	16781	20966	25756	2561	6492	14554	-	10000
		YOUNG FAMILIES -	1996	11142	3330	17887	1925	16547	18819	23734	3099	5540	11657	-	5000
	YOU	JNG SINGLES/COUPLES -	1062	9846	3219	12352	1319	12354	15250	18015	1803	4930	10882		
			90g	110g	134g	150g	160g	165g weight	170g	17 <sup>5</sup> 5g	200g	330g	380g		

2

Out[52]:		premium_customer	lylty_card_nbr	tot_sales	sum_by_clients
	0	Budget	17451	241698.65	13.850132
	1	Mainstream	19836	264108.80	13.314620
	1	Mainstream	19836	264108.80	13.314620

Premium

```
In [53]: # sales by customer status
    chips_products.groupby(['premium_customer']).agg(
        total_sales=('tot_sales', 'sum'),
        average_sales =('tot_sales', 'mean'),
        total_qty=('prod_qty', 'sum'),
        average_qty=('prod_qty', 'mean'),
        count_sales=('tot_sales', 'count')).sort_values(by='count_sales', ascending=Fales)
```

13283 180076.25

# Out[53]:

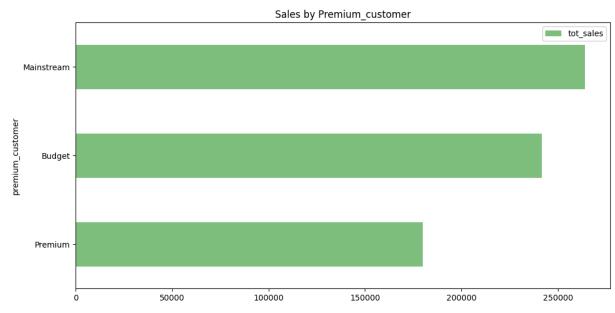
premium\_customer

### total\_sales average\_sales total\_qty average\_qty count\_sales

13.556896

Mainstream	264108.80	6.806051	73774	1.901147	38805
Budget	241698.65	6.671782	69023	1.905292	36227
Premium	180076.25	6.681369	51306	1.903606	26952

Out[54]: <Axes: title={'center': 'Sales by Premium\_customer'}, ylabel='premium\_customer'>



```
In [55]: # sales by brand
    chips_products.groupby(['brand']).agg(
        total_sales=('tot_sales', 'sum'),
```

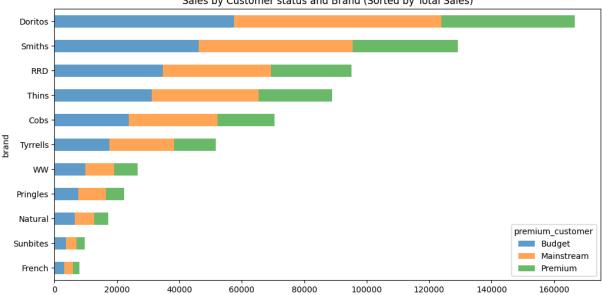
```
average_sales =('tot_sales','mean'),
total_qty=('prod_qty', 'sum'),
average_qty=('prod_qty', 'mean'),
count_sales = ('tot_sales', 'count')).sort_values(by='count_sales', ascending=F
```

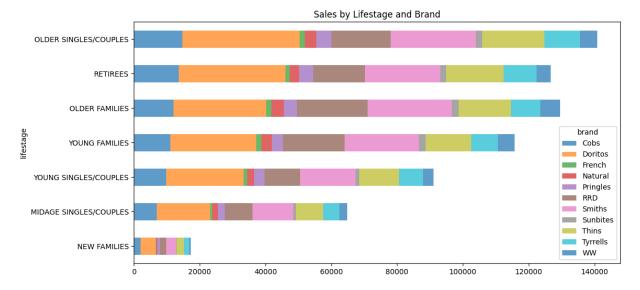
### Out[55]: total\_sales average\_sales total\_qty average\_qty count\_sales

brand					
Doritos	166649.3	8.744781	36498	1.915202	19057
RRD	95046.0	5.345970	33646	1.892457	17779
Smiths	129237.8	7.659898	31999	1.896574	16872
Thins	88852.5	6.312789	26929	1.913250	14075
Cobs	70569.8	7.280491	18571	1.915919	9693
ww	26655.1	3.581231	14029	1.884858	7443
Tyrrells	51647.4	8.017293	12298	1.909034	6442
Pringles	22355.4	7.081216	6043	1.914159	3157
Natural	17265.0	5.679276	5755	1.893092	3040
Sunbites	9676.4	3.216888	5692	1.892287	3008
French	7929.0	5.591678	2643	1.863893	1418

```
In [56]: pivot_brand_customer = chips_products.pivot_table(
             index='brand',
             columns='premium_customer',
             values='tot_sales',
             aggfunc='sum'
         # Sort by premium_customer
         pivot_sorted = pivot_brand_customer.sort_values(by=pivot_brand_customer.columns.tol
                                        ascending=True,
                                        axis=0) # sort by index (rows)
         pivot_sorted.plot(
             figsize=(12, 6),
             kind='barh',
             stacked=True,
             alpha=0.7,
             title='Sales by Customer status and Brand (Sorted by Total Sales)'
         plt.show()
```







```
In [58]: pivot_brands_lifestage_qty = chips_products.pivot_table(
    index='brand',
    columns='lifestage',
    values='prod_qty',
```

```
aggfunc={'sum'}
)
```

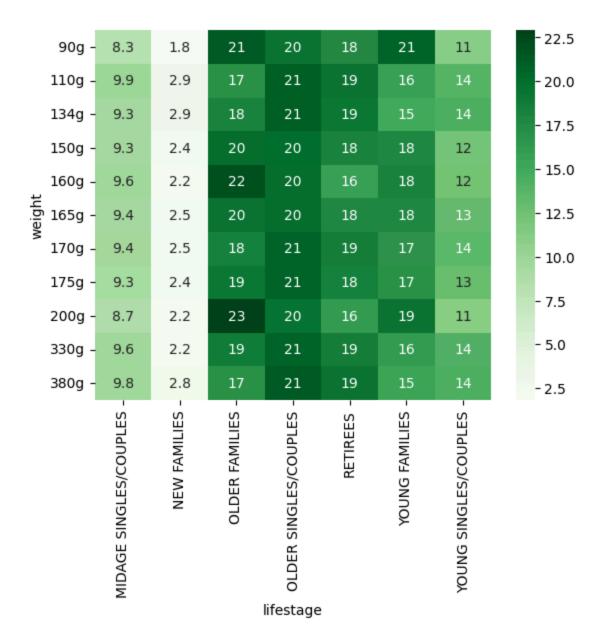
```
In [59]: plt.figure(figsize=(12, 6))
    sns.heatmap(pivot_brands_lifestage_qty, annot=True, fmt='.0f', cmap='Greens', cbar=
    plt.title('Count pachages by Brand and Lifestage');
```

Count pachages by Brand and Lifestage											
Cobs -	1841	542	3165	3898	3602	2932	2591				
Doritos -	3574	1019	6164	7788	7089	5719	5145	- 7000			
French -	218	56	544	522	423	541	339	- 6000			
Natural -	546	119	1235	1143	966	1059	687	- 5000			
Pringles -	565	177	1091	1278	1162	900	870	- 5000			
- DRR pd	3001	703	7596	6320	5570	6613	3843	- 4000			
Smiths -	3028	702	6552	6365	5542	5810	4000	- 3000			
Sunbites -	470	104	1206	1111	1002	1174	625				
Thins -	2506	705	4821	5723	5306	4218	3650	- 2000			
Tyrrells -	1158	354	2120	2574	2394	1933	1765	- 1000			
WW -	1269	312	3163	2759	2239	2644	1643				
	sum-MIDAGE SINGLES/COUPLES -	sum-NEW FAMILIES -	sum-OLDER FAMILIES -	None-lifestage	sum-RETIREES -	sum-YOUNG FAMILIES -	sum-YOUNG SINGLES/COUPLES -				

```
aggfunc='sum',
percentage_total = pivot.div(pivot.sum().sum()) * 100
percentage_by_column = pivot.apply(lambda x: x/x.sum() * 100)
percentage_by_row = pivot.apply(lambda x: x/x.sum() * 100, axis=1)
percentage_total = percentage_total.round(2)
percentage_by_column = percentage_by_column.round(2)
percentage_by_row = percentage_by_row.round(2)
percentage_total_2 = pivot_2.div(pivot_2.sum().sum()) * 100
percentage_by_column_2 = pivot_2.apply(lambda x: x/x.sum() * 100)
percentage_by_row_2 = pivot_2.apply(lambda x: x/x.sum() * 100, axis=1)
percentage_total_2 = percentage_total_2.round(2)
percentage_by_column_2 = percentage_by_column_2.round(2)
percentage_by_row_2 = percentage_by_row_2.round(2)
percentage_total_3 = pivot_3.div(pivot_3.sum().sum()) * 100
percentage_by_column_3 = pivot_3.apply(lambda x: x/x.sum() * 100)
percentage_by_row_3 = pivot_3.apply(lambda x: x/x.sum() * 100, axis=1)
percentage_total_3 = percentage_total_3.round(2)
percentage_by_column_3 = percentage_by_column_3.round(2)
percentage_by_row_3 = percentage_by_row_3.round(2)
```

```
In [61]: sns.heatmap(percentage_by_row_3, annot=True, cmap='Greens')
```

Out[61]: <Axes: xlabel='lifestage', ylabel='weight'>



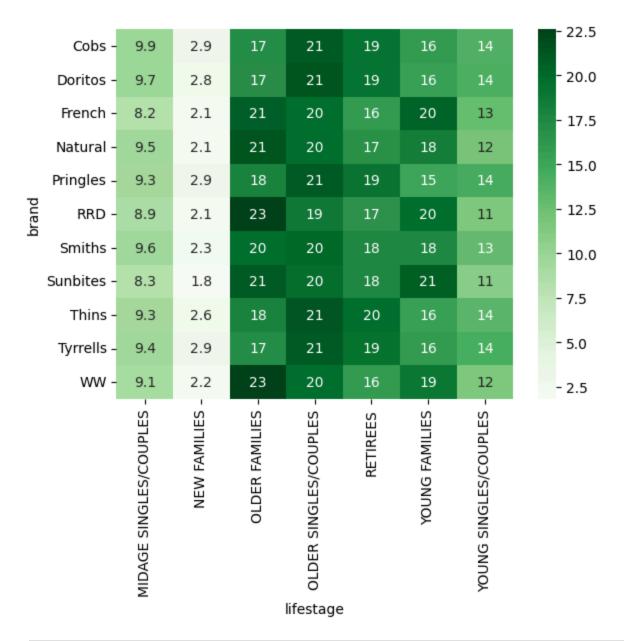
In [62]: percentage\_total.sum(axis=1).sort\_values(ascending=False)

```
Out[62]:
          brand
          Doritos
                       24.30
          Smiths
                       18.85
          RRD
                       13.86
          Thins
                       12.95
          Cobs
                       10.30
          Tyrrells
                        7.53
          WW
                        3.88
          Pringles
                        3.26
          Natural
                        2.51
          Sunbites
                        1.41
                        1.15
          French
          dtype: float64
```

In [63]: percentage\_total.sum(axis=0).sort\_values(ascending=False)

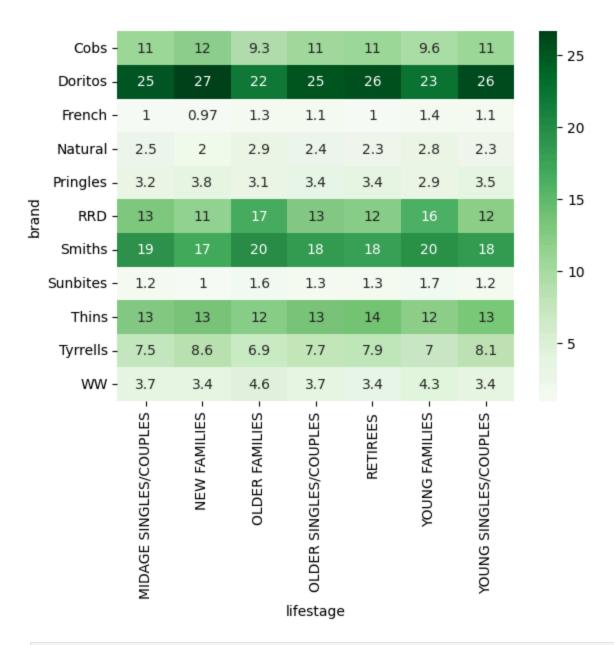
```
Out[63]: premium_customer
         Mainstream
                       38.50
         Budget
                       35.23
         Premium
                       26.27
         dtype: float64
In [64]: percentage_total_2.sum(axis=0).sort_values(ascending=False)
Out[64]: lifestage
         OLDER SINGLES/COUPLES
                                  20.53
         OLDER FAMILIES
                                  18.88
         RETIREES
                                  18.49
         YOUNG FAMILIES
                                  16.87
         YOUNG SINGLES/COUPLES
                                  13.28
         MIDAGE SINGLES/COUPLES
                                  9.47
         NEW FAMILIES
                                   2.55
         dtype: float64
In [65]: sns.heatmap(percentage_by_row_2, annot=True, cmap='Greens')
```

Out[65]: <Axes: xlabel='lifestage', ylabel='brand'>



```
In [66]: sns.heatmap(percentage_by_column_2, annot=True, cmap='Greens')
```

Out[66]: <Axes: xlabel='lifestage', ylabel='brand'>



In [67]: chips\_products.to\_csv('.\\data\\QVI\_chips\_products\_result.csv', index=False)

# **Results**

More than all sales in medium-sized packs. Top 5 weights by sales amount:

- 175g 20.3%
- 170g 16.3%
- 150g 14.6%
- 165g 13.6%
- 380g 10.9%

Before Christmas, sales increase, after Christmas in February there was a noticeable decline. At Christmas, the stores did not work.

Purchases do not differ in customer status, but more sales to groups with Mainstream status due to the fact that there are more of them.

Older families and young families have similar preferences and they differ from the preferences of other groups. These two groups spend more on chips per customer, and made an average of 2.5 purchases per customer per year. They are also more inclined to buy brands such as RRD and Smith.

The main clients of chips are old and young families, pensioners and old single people. Full distribution of sales by groups:

- OLDER SINGLES/COUPLES 20.53%
- OLDER FAMILIES 18.88%
- RETIREES 18.49%
- YOUNG FAMILIES 16.87%
- YOUNG SINGLES/COUPLES 13.28%
- MIDAGE SINGLES/COUPLES 9.47%
- NEW FAMILIES 2.55%

Top 5 brands in terms of sales:

- Doritos 24.30%
- Smiths 18.85%
- RRD 13.86%
- Thins 12.95%
- Cobs 10.30%

## Recommendation

- Arrange shelves with chips closer to the goods that are inherent in shopping for couples.
- Offer chips as a complement to family packs.
- Make themed stands for watching movies with drinks and chips.