Data preparation and customer analytics

In [ ]:
```
# Load required packages
import numpy as np
import pandas as pd
import datetime
import matplotlib.pyplot as plt
```

In [ ]:
```
# Load data
transactions = pd.read_excel('QVI_transaction_data.xlsx')
customers = pd.read_csv('QVI_purchase_behaviour.csv')
```

Examining transactions data

In [ ]:
```
transactions.head()
```

Out[ ]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES
0	43390	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0
1	43599	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3
2	43605	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9
3	43329	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	15.0
4	43330	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	13.8

In [ ]:
```
transactions.info()
# No missing values
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264836 entries, 0 to 264835
Data columns (total 8 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   DATE            264836 non-null  int64  
 1   STORE_NBR       264836 non-null  int64  
 2   LYLTY_CARD_NBR  264836 non-null  int64  
 3   TXN_ID          264836 non-null  int64  
 4   PROD_NBR        264836 non-null  int64  
 5   PROD_NAME       264836 non-null  object 
 6   PROD_QTY        264836 non-null  int64  
 7   TOT_SALES       264836 non-null  float64
dtypes: float64(1), int64(6), object(1)
memory usage: 16.2+ MB
```

In [ ]:

```
transactions.describe()
# We can see that the max value for PROD_QTY is 200, which is large.
```

Out[ ]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_QTY	TOT_SALES
count	264836.000000	264836.00000	2.648360e+05	2.648360e+05	264836.000000	264836.000000	264836.000000
mean	43464.036260	135.08011	1.355495e+05	1.351583e+05	56.583157	1.907309	7.304200
std	105.389282	76.78418	8.057998e+04	7.813303e+04	32.826638	0.643654	3.083226
min	43282.000000	1.00000	1.000000e+03	1.000000e+00	1.000000	1.000000	1.500000
25%	43373.000000	70.00000	7.002100e+04	6.760150e+04	28.000000	2.000000	5.400000
50%	43464.000000	130.00000	1.303575e+05	1.351375e+05	56.000000	2.000000	7.400000
75%	43555.000000	203.00000	2.030942e+05	2.027012e+05	85.000000	2.000000	9.200000
max	43646.000000	272.00000	2.373711e+06	2.415841e+06	114.000000	200.000000	650.000000

In [ ]:

```
transactions.describe(include='object')
```

Out[ ]:

	PROD_NAME
count	264836
unique	114
top	Kettle Mozzarella Basil & Pesto 175g
freq	3304

Checking outliers

In [ ]:

```
transactions.reset_index(drop=True, inplace=True)
print(transactions.PROD_QTY.unique())
# there are one unique value of 200, which is likely to be outliers
transactions[transactions.PROD_QTY == 200]
```

```
[  2   3   5   1   4 200]
```

Out[ ]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES
69762	43331	226	226000	226201	4	Dorito Corn Chp Supreme 380g	200	650.0
69763	43605	226	226000	226210	4	Dorito Corn Chp Supreme 380g	200	650.0

In [ ]:

```
# checking the customer that made these transactions
transactions[transactions.LYLTY_CARD_NBR == 226000]
# it seems that the customer only made these two transactions, we can remove this customer
```

Out[ ]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES
69762	43331	226	226000	226201	4	Dorito Corn Chp Supreme 380g	200	650.0
69763	43605	226	226000	226210	4	Dorito Corn Chp Supreme 380g	200	650.0

In [ ]:

```
# remove the outliers
transactions = transactions[transactions.PROD_QTY != 200]
```

```
# or transactions = transactions[transactions.LYLTY_CARD_NBR != 226000] can also be used
transactions.reset_index(drop=True, inplace=True)
transactions.PROD_QTY.unique()
```

Out[ ]:
```
array([2, 3, 5, 1, 4], dtype=int64)
```

Converting datetime

In [ ]:
```
# Convert DATE column to datetime
transactions.DATE = pd.to_datetime(transactions.DATE, unit='D', origin=datetime.date(1899, 12, 30))
```

Examining false entries

In [ ]:
```
# create a list of individual words in PROD_NAME
words = []
for i in transactions.PROD_NAME:
    words.append(i.split())
# remove all words with digits and special characters such as '&' and '/'
for i in range(len(words)):
    words[i] = [word for word in words[i] if word.isalpha()]
# flatten the list
words = [word for sublist in words for word in sublist]
pd.Series(words).unique()
```

Out[ ]:
```
array(['Natural', 'Chip', 'Compny', 'CCs', 'Nacho', 'Cheese', 'Smiths',
       'Crinkle', 'Cut', 'Chips', 'Chicken', 'Thinly', 'Kettle',
       'Tortilla', 'Chili', 'Old', 'El', 'Paso', 'Salsa', 'Dip', 'Tomato',
       'Mild', 'Salt', 'Vinegar', 'Grain', 'Waves', 'Sweet', 'Chilli',
       'Doritos', 'Corn', 'Mexican', 'Jalapeno', 'Sour', 'Sensations',
       'Siracha', 'Lime', 'Twisties', 'WW', 'Thins', 'Tangy', 'Original',
       'Burger', 'Rings', 'NCC', 'Cream', 'Garden', 'Chives', 'Southern',
       'Cheezels', 'Box', 'Infzns', 'Crn', 'Crnchers', 'Gcamole', 'Sea',
       'And', 'Red', 'Rock', 'Deli', 'Thai', 'Pringles', 'Sthrn',
       'FriedChicken', 'BBQ', 'SR', 'Mzzrlla', 'Originl', 'saltd', 'Sp',
       'Truffle', 'Swt', 'Mexicana', 'French', 'OnionDip', 'ChipCo',
       'Hony', 'Soy', 'Dorito', 'Chp', 'Supreme', 'Roast', 'Mozzarella',
       'Basil', 'Pesto', 'Infuzions', 'SweetChili', 'PotatoMix',
       'Camembert', 'Fig', 'Smith', 'Mac', 'N', 'Honey',
       'Seasonedchicken', 'Rib', 'Prawn', 'Crackers', 'GrnWves', 'Plus',
       'Btroot', 'Jam', 'Tyrrells', 'Crisps', 'Lightly', 'Salted',
       'Medium', 'Pot', 'SourCream', 'Onion', 'Chnky', 'Tom', 'Cobs',
       'Popd', 'Woolworths', 'Co', 'Tmato', 'Fries', 'Potato', 'Med',
       'RRD', 'Coconut', 'Hot', 'Spicy', 'Crm', 'Crnkle', 'Orgnl', 'Big',
       'Bag', 'Crips', 'Stacked', 'Tostitos', 'Barbecue', 'Cheetos',
       'Puffs', 'Splash', 'Of', 'Tasty', 'Smoked', 'Chipotle', 'Barbeque',
       'Mystery', 'Flavour', 'Ched', 'Snbts', 'Whlgrn', 'Chs', 'Bacon',
       'Balls', 'Slt', 'Vingar', 'Veg', 'Strws', 'Mango', 'Chutny',
       'Papadums', 'Steak', 'Chimuchurri', 'Sunbites', 'Whlegrn',
       'Pepper', 'Vinegr', 'Aioli', 'Slow', 'Rst', 'Pork', 'Belly', 'Pc',
       'Bolognese'], dtype=object)
```

In [ ]:
```
pd.Series(words).value_counts().head(20)
```

Out[ ]:
```
Chips       49770
Kettle      41288
Smiths      28860
Salt        27976
Cheese      27890
Pringles    25102
Doritos     24962
Crinkle     23960
Corn        22061
Original    21560
Cut         20754
Chip        18645
Salsa       18094
Chicken     15407
Sea         14145
Thins       14075
Sour        13882
Crisps      12607
Vinegar     12402
Chilli      12389
Name: count, dtype: int64
```

As we can see from the previous two codel cells, there are salsa products in the dataset, which is not the item of interest.

In [ ]:
```
# remove salsa products
transactions = transactions[~transactions.PROD_NAME.str.contains('Salsa')]
# check if salsa products are removed
transactions[transactions.PROD_NAME.str.contains('Salsa')].shape
```

Out[ ]:
```
(0, 8)
```

Salsa products are removed since the shape is (0, 8) which means there are 0 rows and 8 columns

---

Missing dates

In [ ]:
```python
transactions.DATE.value_counts().sort_index()
# the data is from 2018-07-01 to 2019-06-30 with 364 days in total, indicates that there is one day missing
```

Out[ ]:
```
DATE
2018-07-01    663
2018-07-02    650
2018-07-03    674
2018-07-04    669
2018-07-05    660
             ...
2019-06-26    657
2019-06-27    669
2019-06-28    673
2019-06-29    703
2019-06-30    704
Name: count, Length: 364, dtype: int64
```

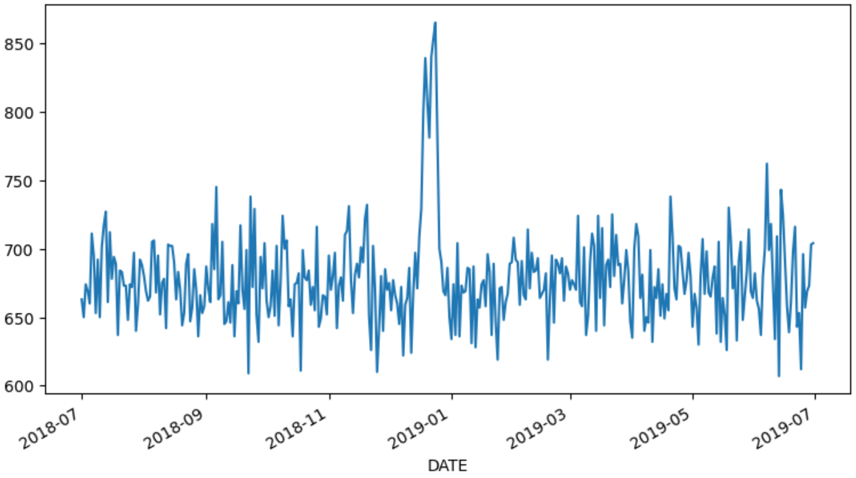
In [ ]:
```python
# find the missing date
pd.date_range(start='2018-07-01', end='2019-06-30').difference(transactions.DATE)
```

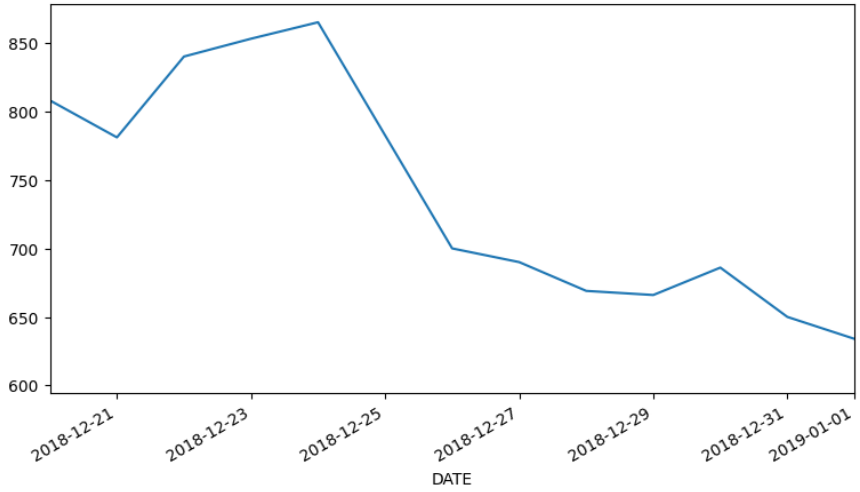
Out[ ]:
```
DatetimeIndex(['2018-12-25'], dtype='datetime64[ns]', freq=None)
```

In [ ]:
```python
# double-check by zooming in on the date range from 2018-12-20 to 2019-01-01
transactions.DATE[(transactions.DATE >= '2018-12-20') & (transactions.DATE <= '2019-01-01')].value_counts().sort_index()
# there is indeed one day missing: 2018-12-25
```

Out[ ]:
```
DATE
2018-12-20    808
2018-12-21    781
2018-12-22    840
2018-12-23    853
2018-12-24    865
2018-12-26    700
2018-12-27    690
2018-12-28    669
2018-12-29    666
2018-12-30    686
2018-12-31    650
2019-01-01    634
Name: count, dtype: int64
```

In [ ]:
```
# create a plot containing two subplots
fig, ax = plt.subplots(1, 2, figsize=(20, 5))

# we can also check the missing date by creating a chart of the number of transactions over time
transactions.DATE.value_counts().sort_index().plot(ax=ax[0])

# zoom in on the missing date
transactions.DATE.value_counts().sort_index().plot(ax=ax[1])
ax[1].set_xlim(pd.Timestamp('2018-12-20'), pd.Timestamp('2019-01-01'))

plt.show()
```





Looking at the visualisations, we can see a decrease from 2018-12-24 to 2018-12-26 without any break in the line lead to 2018-12-26, indicates that there are no sale made on 2018-12-25, the Christmas day. The descriptive statistics created before this also confirm this statement.

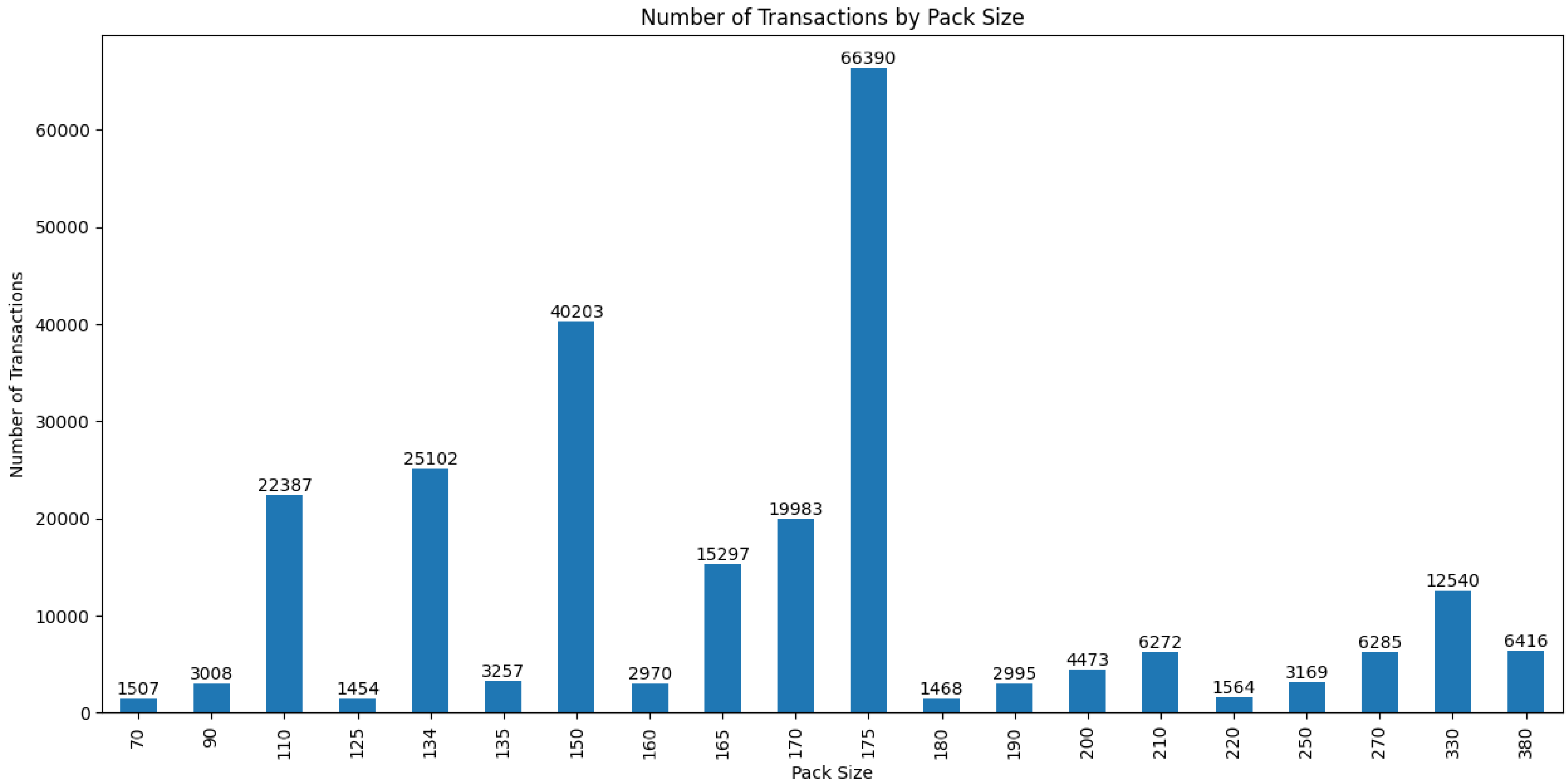
Creating new columns

In [ ]:
```
# create a column of pack size for each product
transactions['PACK_SIZE'] = transactions.PROD_NAME.str.extract('(\d+)')
transactions.PACK_SIZE = transactions.PACK_SIZE.astype('int64')
```

In [ ]:
```
# remove the last 4 characters from PROD_NAME
transactions.PROD_NAME = transactions.PROD_NAME.str[:-4]
transactions.PROD_NAME = transactions.PROD_NAME.str.strip()
transactions.PROD_NAME
```

```
Out[ ]: 0            Natural Chip        Compny SeaSalt
        1                              CCs Nacho Cheese
        2             Smiths Crinkle Cut  Chips Chicken
        3             Smiths Chip Thinly  S/Cream&Onion
        4           Kettle Tortilla ChpsHny&Jlpno Chili
                                       ...
        264829     Kettle Sweet Chilli And Sour Cream
        264830               Tostitos Splash Of  Lime
        264831                       Doritos Mexicana
        264832     Doritos Corn Chip Mexican Jalapeno
        264833               Tostitos Splash Of  Lime
        Name: PROD_NAME, Length: 246740, dtype: object
```

```
In [ ]: # create a chart showing the number of transactions by pack size.
ax = transactions.PACK_SIZE.value_counts().sort_index().plot(kind='bar', figsize=(15, 7))
plt.xlabel('Pack Size')
plt.ylabel('Number of Transactions')
plt.title('Number of Transactions by Pack Size')
ax.bar_label(ax.containers[0], label_type="edge")
plt.show()
```



Based on the chart, we can see that there are 4 most popular pack sizes. In order, 175g, 150g, 134g, 110g

In [ ]:
```
# create a column of brand name for each product
dict = {'RRD': 'Red Rock Deli', 'WW': 'Woolworths', 'NCC': 'Natural Chip Co', r'\bSmith\b': 'Smiths', 'Infzns': 'Infuzions', '
        'GrnWves':'Grain Waves'}
transactions.PROD_NAME.replace(dict, regex=True, inplace=True)
transactions['BRAND'] = transactions.PROD_NAME.str.split().str[0]
transactions.BRAND.value_counts()
```

Out[ ]:
```
BRAND
Kettle        41288
Smiths        30353
Pringles      25102
Doritos       22041
Red           16321
Infuzions     14201
Thins         14075
Woolworths    11836
Cobs           9693
Tostitos       9471
Twisties       9454
Grain          7740
Natural        7469
Tyrrells       6442
Cheezels       4603
CCs            4551
Dorito         3183
Sunbites       3008
Cheetos        2927
Burger         1564
French         1418
Name: count, dtype: int64
```

In [ ]:
```
transactions
```

Out[ ]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	BRAND
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt	2	6.0	175	Natural
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese	3	6.3	175	CCs
2	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken	2	2.9	170	Smiths
3	2018-08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion	5	15.0	175	Smiths
4	2018-08-18	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili	3	13.8	150	Kettle
...	...	...	...	...	...	...	...	...	...	...
264829	2019-03-09	272	272319	270088	89	Kettle Sweet Chilli And Sour Cream	2	10.8	175	Kettle
264830	2018-08-13	272	272358	270154	74	Tostitos Splash Of Lime	1	4.4	175	Tostitos
264831	2018-11-06	272	272379	270187	51	Doritos Mexicana	2	8.8	170	Doritos
264832	2018-12-27	272	272379	270188	42	Doritos Corn Chip Mexican Jalapeno	2	7.8	150	Doritos
264833	2018-09-22	272	272380	270189	74	Tostitos Splash Of Lime	2	8.8	175	Tostitos

246740 rows × 10 columns

Examining customers data

In [ ]:

```
customers.head()
```

Out[ ]:

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER
0	1000	YOUNG SINGLES/COUPLES	Premium
1	1002	YOUNG SINGLES/COUPLES	Mainstream
2	1003	YOUNG FAMILIES	Budget
3	1004	OLDER SINGLES/COUPLES	Mainstream
4	1005	MIDAGE SINGLES/COUPLES	Mainstream

In [ ]:

```
customers.info()
# No missing values
```

```
<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
 2   PREMIUM_CUSTOMER  72637 non-null  object
dtypes: int64(1), object(2)
memory usage: 1.7+ MB
```

In [ ]:

```
customers.describe(include='all')
```

Out[ ]:

	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 [ ]:

```
customers.LYLTY_CARD_NBR.value_counts()
# There are 72637 unique customers, with no duplicates
```

Out[ ]:

```
LYLTY_CARD_NBR
1000       1
181211     1
181217     1
181216     1
181215     1
          ..
88126      1
88127      1
88128      1
88129      1
2373711    1
Name: count, Length: 72637, dtype: int64
```

In [ ]:
```
customers.LIFESTAGE.value_counts()
# There are 7 unique lifestages
```

Out[ ]:
```
LIFESTAGE
RETIREES                  14805
OLDER SINGLES/COUPLES     14609
YOUNG SINGLES/COUPLES     14441
OLDER FAMILIES             9780
YOUNG FAMILIES             9178
MIDAGE SINGLES/COUPLES     7275
NEW FAMILIES               2549
Name: count, dtype: int64
```

In [ ]:
```
customers.PREMIUM_CUSTOMER.value_counts()
# There are 3 unique premium customers
```

Out[ ]:
```
PREMIUM_CUSTOMER
Mainstream    29245
Budget        24470
Premium       18922
Name: count, dtype: int64
```

We can see that there are 3 unique premium customers and 7 unique lifestages, which means there are 21 unique customer segments

In [ ]:
```
# merge the two datasets, keeping all the rows of transactions on the left and find rows with matching values from customers o
data = pd.merge(transactions, customers, on='LYLTY_CARD_NBR', how='left')
data.head()
```

Out[ ]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	BRAND	LIFEST
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt	2	6.0	175	Natural	YOU SINGLES/COU
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese	3	6.3	175	CCs	MID SINGLES/COU
2	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken	2	2.9	170	Smiths	MID SINGLES/COU
3	2018-08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion	5	15.0	175	Smiths	MID SINGLES/COU
4	2018-08-18	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili	3	13.8	150	Kettle	MID SINGLES/COU

In [ ]:

```
# Check on any missing values
data.isnull().sum()
# There are 0 missing values
```

Out[ ]:

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

In [ ]:

```python
# Export the data to a csv file
data.to_csv('data.csv', index=False)
```

Data Analysis

Who spends the most on chips (total sales)? Their lifestages, and general purchasing behaviour?

In [ ]:

```python
sales_by_cus = data.groupby('LYLTY_CARD_NBR')[['TOT_SALES','LIFESTAGE', 'PREMIUM_CUSTOMER']].agg(
    {'TOT_SALES': 'sum', 'LIFESTAGE': 'first', 'PREMIUM_CUSTOMER': 'first'}
).sort_values(by='TOT_SALES', ascending=False)

sale_summary_segment = pd.merge(
    sales_by_cus[['PREMIUM_CUSTOMER','LIFESTAGE']].value_counts().to_frame(),
    sales_by_cus.groupby(['PREMIUM_CUSTOMER','LIFESTAGE']).TOT_SALES.sum().sort_values(ascending=False).to_frame(),
    left_index=True, right_index=True
)
sale_summary_segment.rename(columns={'count': 'Number of Customer', 'TOT_SALES': 'Total Sales'}, inplace=True)
sale_summary_segment['Average Sales per Customer'] = sale_summary_segment['Total Sales'] / sale_summary_segment['Number of Cus
# To change the sort column, we can replace the by argument with one of the three column names
sale_summary_segment.sort_values(by='Total Sales', ascending=False)
```

Out[ ]:

PREMIUM_CUSTOMER	LIFESTAGE	Number of Customer	Total Sales	Average Sales per Customer
Budget	OLDER FAMILIES	4611	156863.75	34.019464
Mainstream	YOUNG SINGLES/COUPLES	7917	147582.20	18.641177
Mainstream	RETIREES	6358	145168.95	22.832487
Budget	YOUNG FAMILIES	3953	129717.95	32.815065
Budget	OLDER SINGLES/COUPLES	4849	127833.60	26.362879
Mainstream	OLDER SINGLES/COUPLES	4858	124648.50	25.658399
Premium	OLDER SINGLES/COUPLES	4682	123537.55	26.385636
Budget	RETIREES	4385	105916.30	24.154230
Mainstream	OLDER FAMILIES	2788	96413.55	34.581618
Premium	RETIREES	3812	91296.65	23.949803
Mainstream	YOUNG FAMILIES	2685	86338.25	32.155773
Mainstream	MIDAGE SINGLES/COUPLES	3298	84734.25	25.692617
Premium	YOUNG FAMILIES	2398	78571.70	32.765513
Premium	OLDER FAMILIES	2231	75242.60	33.725952
Budget	YOUNG SINGLES/COUPLES	3647	57122.10	15.662764
Premium	MIDAGE SINGLES/COUPLES	2369	54443.85	22.981786
Premium	YOUNG SINGLES/COUPLES	2480	39052.30	15.746895
Budget	MIDAGE SINGLES/COUPLES	1474	33345.70	22.622592
Budget	NEW FAMILIES	1087	20607.45	18.958096
Mainstream	NEW FAMILIES	830	15979.70	19.252651
Premium	NEW FAMILIES	575	10760.80	18.714435

Some of the findings are:

- The main customer segment is from Mainstream - Young singles/couples, Mainstream - Retirees, Budget - Older families, and all of the Older singles/couples. Same story for the total sales
- But with average Sales per Customer, the older and young families dominate the table, indicating that in the customer segment, in general, each customer willing to but more chips and make higher sale.

In [ ]:

```
# since older families and young families are not so different in Average Sales per Customer, the difference is checked by t-t
import scipy.stats as stats
stats.ttest_ind(data[data['LIFESTAGE'] == 'OLDER FAMILIES']['TOT_SALES'],
                data[data['LIFESTAGE'] == 'YOUNG FAMILIES']['TOT_SALES'])
```

Out[ ]:

```
TtestResult(statistic=-0.056587603083385794, pvalue=0.9548738420247515, df=85650.0)
```

There aren't any statistically significant difference in the Total Sales between Older and Young Families.

In [ ]:

```
# create a dataframe of total sales larger than 100 dollars
sales_larger_than_100 = sales_by_cus[sales_by_cus.TOT_SALES > 100]
sales_larger_than_100
```

Out[ ]:

LYLTY_CARD_NBR	TOT_SALES	LIFESTAGE	PREMIUM_CUSTOMER
230078	138.6	OLDER FAMILIES	Budget
58361	124.8	YOUNG FAMILIES	Budget
63197	122.6	OLDER FAMILIES	Budget
162039	121.6	OLDER FAMILIES	Mainstream
179228	120.8	YOUNG FAMILIES	Budget
...	...	...	...
48155	100.7	OLDER SINGLES/COUPLES	Budget
209155	100.6	YOUNG FAMILIES	Budget
67109	100.4	RETIREES	Premium
226215	100.4	OLDER FAMILIES	Premium
138222	100.3	OLDER FAMILIES	Budget

72 rows × 3 columns

Based on the table above, we can see that the highest customer spent 138.6 dollars in total and the customer with loyalty number 230078 is from the 'OLDER FAMILIES' lifestage and belongs to the 'Budget' customer segment.

In [ ]:

```
sales_larger_than_100[['PREMIUM_CUSTOMER','LIFESTAGE']].value_counts().sort_index()
```

```
Out[ ]: PREMIUM_CUSTOMER  LIFESTAGE
        Budget            OLDER FAMILIES            11
                          OLDER SINGLES/COUPLES      5
                          RETIREES                   3
                          YOUNG FAMILIES            15
                          YOUNG SINGLES/COUPLES      2
        Mainstream        MIDAGE SINGLES/COUPLES     1
                          OLDER FAMILIES             8
                          OLDER SINGLES/COUPLES      2
                          YOUNG FAMILIES             2
                          YOUNG SINGLES/COUPLES      4
        Premium           MIDAGE SINGLES/COUPLES     3
                          OLDER FAMILIES             3
                          OLDER SINGLES/COUPLES      6
                          RETIREES                   1
                          YOUNG FAMILIES             4
                          YOUNG SINGLES/COUPLES      2
        Name: count, dtype: int64
```

In the customer segment where they have made purchases that up to 100 dollars, the two highest customer segment are Budget - Older families and Budget - Young families.

How many transactions are in each segment?

```
In [ ]: cus_by_seg = data.groupby(['PREMIUM_CUSTOMER','LIFESTAGE'])['LYLTY_CARD_NBR'].count()
        # calculating the total of customers of each premium customer segment
        cus_by_seg.groupby('PREMIUM_CUSTOMER').sum()
```

```
Out[ ]: PREMIUM_CUSTOMER
        Budget        86762
        Mainstream    95043
        Premium       64935
        Name: LYLTY_CARD_NBR, dtype: int64
```

```
In [ ]: cus_by_seg.sort_values(ascending=False)
```

```
Out[ ]: PREMIUM_CUSTOMER  LIFESTAGE
        Budget            OLDER FAMILIES            21514
        Mainstream        RETIREES                  19970
                          YOUNG SINGLES/COUPLES     19544
        Budget            YOUNG FAMILIES            17763
                          OLDER SINGLES/COUPLES     17172
        Mainstream        OLDER SINGLES/COUPLES     17061
        Premium           OLDER SINGLES/COUPLES     16560
        Budget            RETIREES                  14225
        Mainstream        OLDER FAMILIES            13241
        Premium           RETIREES                  12236
        Mainstream        YOUNG FAMILIES            11947
                          MIDAGE SINGLES/COUPLES    11095
        Premium           YOUNG FAMILIES            10784
                          OLDER FAMILIES            10403
        Budget            YOUNG SINGLES/COUPLES      8573
        Premium           MIDAGE SINGLES/COUPLES     7612
                          YOUNG SINGLES/COUPLES      5852
        Budget            MIDAGE SINGLES/COUPLES     4691
                          NEW FAMILIES               2824
        Mainstream        NEW FAMILIES               2185
        Premium           NEW FAMILIES               1488
        Name: LYLTY_CARD_NBR, dtype: int64
```

Based on the above descriptive statistics, some findings are:

- The top 3 segments are Budget - Older Families, Mainstream - Retirees, and Mainstream - Young Singles/Couples
- The bottom 3 segments are all NEW FAMILIES

How many chips are bought per customer by segment?

```
In [ ]: chip_by_seg = data.groupby(['PREMIUM_CUSTOMER','LIFESTAGE'])['PROD_QTY'].sum()
        # calculating the total of chips of each premium customer segment
        chip_by_seg.groupby('PREMIUM_CUSTOMER').sum()
```

```
Out[ ]: PREMIUM_CUSTOMER
Budget        165774
Mainstream    180780
Premium       123845
Name: PROD_QTY, dtype: int64
```

```
In [ ]: chip_by_seg.sort_values(ascending=False)
```

```
Out[ ]: PREMIUM_CUSTOMER  LIFESTAGE
Budget            OLDER FAMILIES            41853
Mainstream        RETIREES                  37677
                  YOUNG SINGLES/COUPLES     36225
Budget            YOUNG FAMILIES            34482
                  OLDER SINGLES/COUPLES     32883
Mainstream        OLDER SINGLES/COUPLES     32607
Premium           OLDER SINGLES/COUPLES     31695
Budget            RETIREES                  26932
Mainstream        OLDER FAMILIES            25804
Premium           RETIREES                  23266
Mainstream        YOUNG FAMILIES            23194
                  MIDAGE SINGLES/COUPLES    21213
Premium           YOUNG FAMILIES            20901
                  OLDER FAMILIES            20239
Budget            YOUNG SINGLES/COUPLES     15500
Premium           MIDAGE SINGLES/COUPLES    14400
                  YOUNG SINGLES/COUPLES     10575
Budget            MIDAGE SINGLES/COUPLES     8883
                  NEW FAMILIES               5241
Mainstream        NEW FAMILIES               4060
Premium           NEW FAMILIES               2769
Name: PROD_QTY, dtype: int64
```

The same top 3 and bottom 3 statements are held for the number of chips as well.

What's the average chip price by customer segment?

In [ ]:
```
avg_chip_by_seg = data.groupby(['PREMIUM_CUSTOMER','LIFESTAGE'])['TOT_SALES'].mean()
avg_chip_by_seg
```

Out[ ]:
```
PREMIUM_CUSTOMER  LIFESTAGE
Budget            MIDAGE SINGLES/COUPLES    7.108442
                  NEW FAMILIES              7.297256
                  OLDER FAMILIES            7.291241
                  OLDER SINGLES/COUPLES     7.444305
                  RETIREES                  7.445786
                  YOUNG FAMILIES            7.302705
                  YOUNG SINGLES/COUPLES     6.663023
Mainstream        MIDAGE SINGLES/COUPLES    7.637156
                  NEW FAMILIES              7.313364
                  OLDER FAMILIES            7.281440
                  OLDER SINGLES/COUPLES     7.306049
                  RETIREES                  7.269352
                  YOUNG FAMILIES            7.226772
                  YOUNG SINGLES/COUPLES     7.551279
Premium           MIDAGE SINGLES/COUPLES    7.152371
                  NEW FAMILIES              7.231720
                  OLDER FAMILIES            7.232779
                  OLDER SINGLES/COUPLES     7.459997
                  RETIREES                  7.461315
                  YOUNG FAMILIES            7.285951
                  YOUNG SINGLES/COUPLES     6.673325
Name: TOT_SALES, dtype: float64
```

Based on the descriptive statistics above:

- The range are around 6.66 to 7.63 dollars per segment.
- Overall, the average of chip sales in each segment is similar.

The customer's total spend over the period

In [ ]:
```
# create a dataframe of total transactions and total sales by date
sales_by_date = data.groupby('DATE')[['TOT_SALES','TXN_ID']].agg({'TOT_SALES': 'sum', 'TXN_ID': 'count'})
```

```python
# create a column of average sales by date
sales_by_date['AVG_SALES'] = sales_by_date.TOT_SALES / sales_by_date.TXN_ID
# include sum for all columns
sales_by_date.loc['Total'] = sales_by_date.sum(axis=0)
sales_by_date
```

Out[ ]:

	TOT_SALES	TXN_ID	AVG_SALES
DATE			
2018-07-01 00:00:00	4920.1	663.0	7.420965
2018-07-02 00:00:00	4877.0	650.0	7.503077
2018-07-03 00:00:00	4954.7	674.0	7.351187
2018-07-04 00:00:00	4968.1	669.0	7.426158
2018-07-05 00:00:00	4682.0	660.0	7.093939
...	...	...	...
2019-06-27 00:00:00	4941.3	669.0	7.386099
2019-06-28 00:00:00	4876.6	673.0	7.246062
2019-06-29 00:00:00	5177.6	703.0	7.365007
2019-06-30 00:00:00	5108.4	704.0	7.256250
Total	1805177.7	246740.0	2663.123602

365 rows × 3 columns

In [ ]:

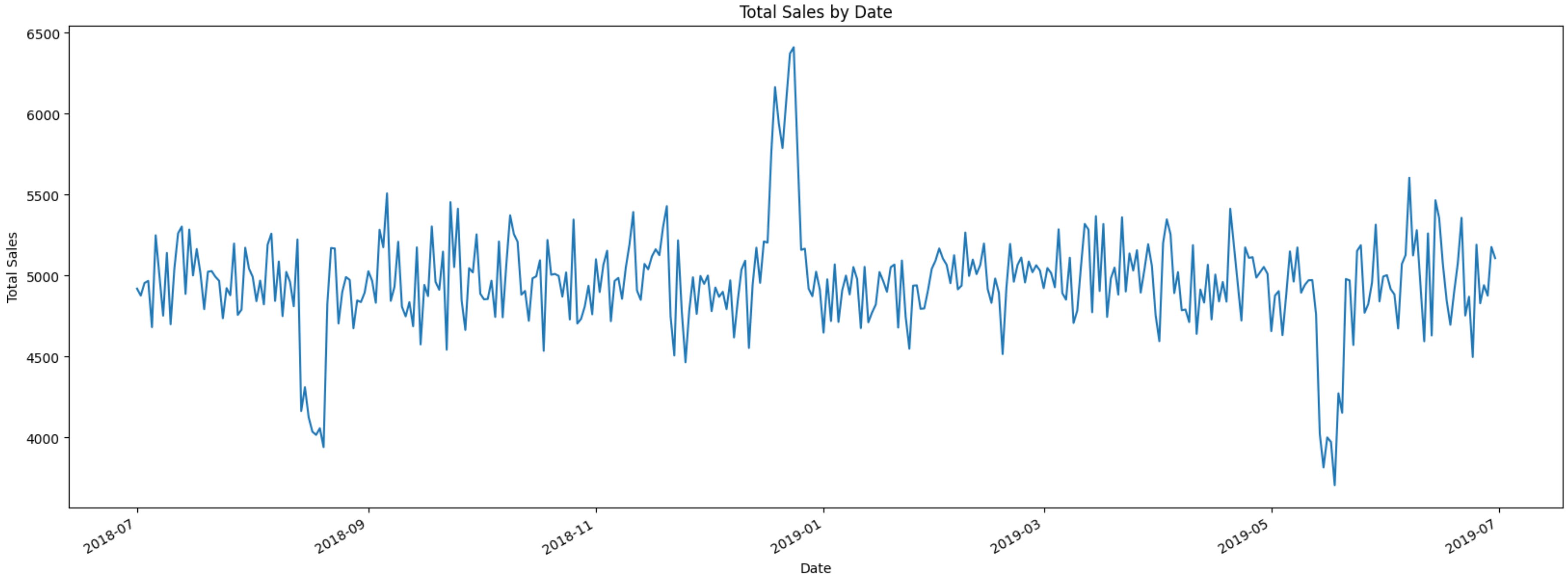
```python
sales_by_date.describe()
```

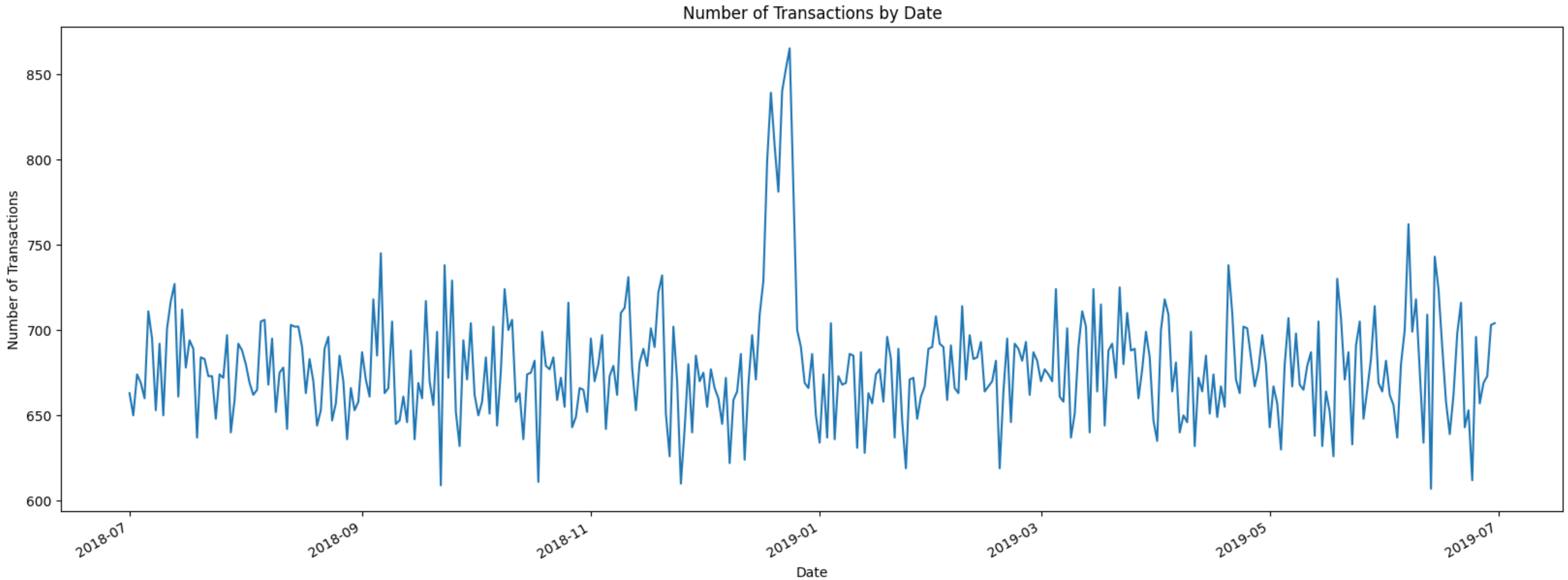
Out[ ]:

	TOT_SALES	TXN_ID	AVG_SALES
count	3.650000e+02	365.000000	365.000000
mean	9.891385e+03	1352.000000	14.592458
std	9.422825e+04	12879.525137	139.011594
min	3.705700e+03	607.000000	5.707163
25%	4.832300e+03	658.000000	7.302914
50%	4.968100e+03	674.000000	7.371231
75%	5.108400e+03	695.000000	7.425575
max	1.805178e+06	246740.000000	2663.123602

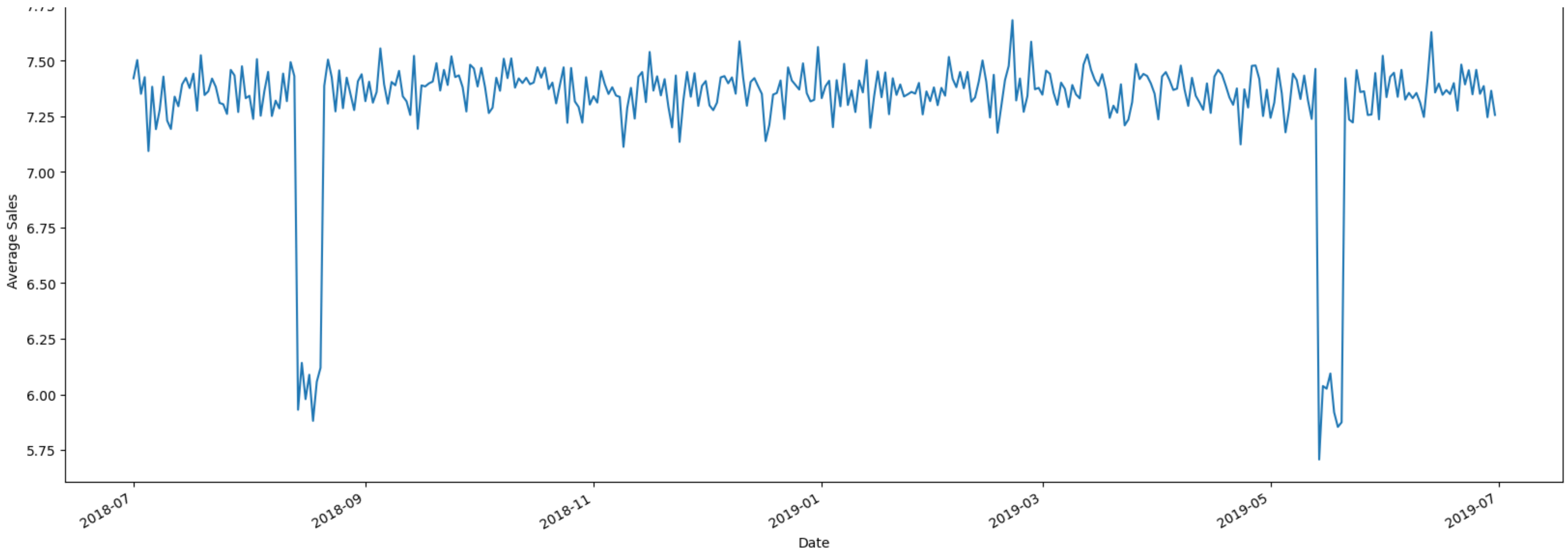
In [ ]:

```
fig, ax = plt.subplots(3,1,figsize=(20, 25))

# create a plot depicting the total spending of customers over time
data.groupby('DATE')['TOT_SALES'].sum().plot(ax=ax[0], xlabel='Date', ylabel='Total Sales', title='Total Sales by Date')

# create a plot depicting the number of transactions over time
data.DATE.value_counts().sort_index().plot(ax=ax[1], xlabel='Date', ylabel='Number of Transactions', title='Number of Transact

# create a plot depicting the average spending of customers over time
sales_by_date[:-1].AVG_SALES.plot(ax=ax[2], xlabel='Date', ylabel='Average Sales', title='Average Sales by Date')

plt.show()
```


Total Sales by Date
Total Sales
6500
6000
5500
5000
4500
4000
2018-07
2018-09
2018-11
2019-01
2019-03
2019-05
2019-07
Date


Number of Transactions by Date
Number of Transactions
850
800
750
700
650
600
2018-07
2018-09
2018-11
2019-01
2019-03
2019-05
2019-07
Date


Average Sales by Date
7.75



Looking at these three plots, some of the findings are:

- In total, the revenue made for selling chips is about 1.8 millions, with about 4959 ± 310 are spent by all customers in one day.
- Each customer usually spend in average 7.1 - 7.6 dollars for chips.
- There is a high amount of transactions in the month December of 2018.
- There are two low selling prices in August 2018 and May 2019 despite the somewhat same amount of transactions.

What are the top-selling chip?

In [ ]:

```
data.PROD_NAME.value_counts().head(10)
```

Out[ ]:

```
PROD_NAME
Kettle Mozzarella   Basil & Pesto      3304
Kettle Tortilla ChpsHny&Jlpno Chili    3296
Cobs Popd Swt/Chlli &Sr/Cream Chips    3269
Tyrrells Crisps     Ched & Chives      3268
Cobs Popd Sea Salt  Chips              3265
Kettle 135g Swt Pot Sea                3257
Tostitos Splash Of  Lime               3252
Infuzions Thai SweetChili PotatoMix    3242
Smiths Crnkle Chip  Orgnl Big Bag      3233
Thins Potato Chips  Hot & Spicy        3229
Name: count, dtype: int64
```

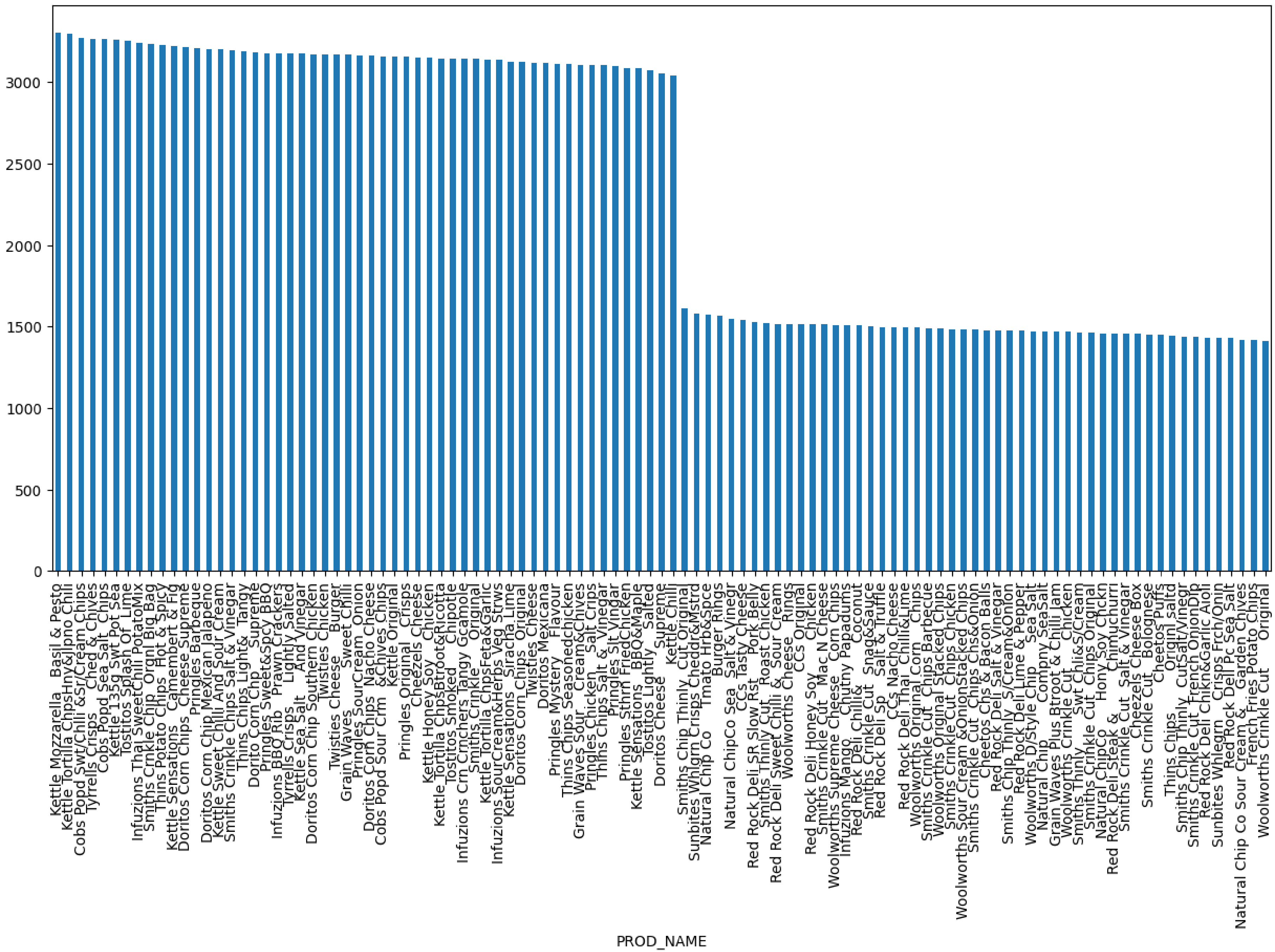
Based on the descriptive statistics, it is obvious that Kettle Mozzarella flavor is the highest, but it is only by a relatively small margin of 10 bags against 2nd place from the same brand.

In [ ]:

```
data.PROD_NAME.value_counts().plot(kind='bar', figsize=(15, 7))
```

Out[ ]:

```
<Axes: xlabel='PROD_NAME'>
```



3000
2500
2000
1500
1000
500
0
Kettle Mozzarella Basil & Pesto
Kettle Tortilla ChpsHny&Jlpno Chili
Cobs Popd Swt/Chlli &Sr/Cream Chips
Tyrrells Crisps Ched & Chives
Cobs Popd Sea Salt Chips
Kettle 135g Swt Pot Sea
Tostitos Splash Of Lime
Infuzions Thai SweetChili PotatoMix
Smiths Crnkle Chip Orgnl Big Bag
Thins Potato Chips Hot & Spicy
Kettle Sensations Camembert & Fig
Doritos Corn Chips Cheese Supreme
Pringles Barbeque
Doritos Corn Chip Mexican Jalapeno
Kettle Sweet Chilli And Sour Cream
Smiths Crinkle Chips Salt & Vinegar
Thins Chips Light& Tangy
Dorito Corn Chp Supreme
Pringles Sweet&Spcy BBQ
Infuzions BBQ Rib Prawn Crackers
Tyrrells Crisps Lightly Salted
Kettle Sea Salt And Vinegar
Doritos Corn Chip Southern Chicken
Twisties Chicken
Twisties Cheese Burger
Grain Waves Sweet Chilli
Pringles SourCream Onion
Doritos Corn Chips Nacho Cheese
Cobs Popd Sour Crm &Chives Chips
Kettle Original
Pringles Original Crisps
Cheezels Cheese
Kettle Honey Soy Chicken
Kettle Tortilla ChpsBtroot&Ricotta
Tostitos Smoked Chipotle
Infuzions Crn Crnchers Tangy Gcamole
Smiths Crinkle Original
Kettle Tortilla ChpsFeta&Garlic
Infuzions SourCream&Herbs Veg Strws
Kettle Sensations Siracha Lime
Doritos Corn Chips Original
Twisties Cheese
Doritos Mexicana
Pringles Mystery Flavour
Thins Chips Seasonedchicken
Grain Waves Sour Cream&Chives
Pringles Chicken Salt Crips
Thins Chips Salt & Vinegar
Pringles Slt Vingar
Pringles Sthrn FriedChicken
Kettle Sensations BBQ&Maple
Tostitos Lightly Salted
Doritos Cheese Supreme
Kettle Chilli
Smiths Chip Thinly Cut Original
Sunbites Whlgrn Crisps Cheddr&Mstrd
Natural Chip Co Tmato Hrb&Spce
Burger Rings
Natural ChipCo Sea Salt & Vinegr
CCs Tasty Cheese
Red Rock Deli SR Slow Rst Pork Belly
Smiths Thinly Cut Roast Chicken
Red Rock Deli Sweet Chilli & Sour Cream
Woolworths Cheese Rings
CCs Original
Red Rock Deli Honey Soy Chicken
Smiths Crinkle Cut Mac N Cheese
Woolworths Supreme Cheese Corn Chips
Infuzions Mango Chutny Papadums
Red Rock Deli Chilli& Coconut
Smiths Crinkle Cut Snag&Sauce
Red Rock Deli Sp Salt & Truffle
CCs Nacho Cheese
Red Rock Deli Thai Chilli&Lime
Woolworths Original Corn Chips
Smiths Crinkle Cut Chips Barbecue
Woolworths Original Stacked Chips
Smiths Crinkle Cut Chips Chicken
Woolworths Sour Cream &OnionStacked Chips
Smiths Crinkle Cut Chips Chs&Onion
Cheetos Chs & Bacon Balls
Red Rock Deli Salt & Vinegar
Smiths Chip Thinly S/Cream&Onion
Red Rock Deli Lime & Pepper
Woolworths D/Style Chip Sea Salt
Natural Chip Compny SeaSalt
Grain Waves Plus Btroot & Chilli Jam
Woolworths Crinkle Cut Chicken
Smiths Thinly Swt Chli&S/Cream
Smiths Crinkle Cut Chips Original
Natural ChipCo Hony Soy Chckn
Red Rock Deli Steak & Chimuchurri
Smiths Crinkle Cut Salt & Vinegar
Cheezels Cheese Box
Smiths Crinkle Cut Bolognese
Cheetos Puffs
Thins Chips Originl saltd
Smiths Chip Thinly CutSalt/Vinegr
Smiths Crinkle Cut French OnionDip
Red Rock Deli Chikn&Garlic Aioli
Sunbites Whlegrn Crisps Frch/Onin
Red Rock Deli Pc Sea Salt
Natural Chip Co Sour Cream & Garden Chives
French Fries Potato Chips
Woolworths Crinkle Cut Original
PROD_NAME

Based on the plot, it is clear that there are no defining top contender. Rather, there are a clear seperation line between two sets of chips.

In [ ]:
```
data[
    data.PROD_NAME.isin(
        data.PROD_NAME.value_counts()[data.PROD_NAME.value_counts() > 3000].index
)].BRAND.value_counts()
```

Out[ ]:
```
BRAND
Kettle       41288
Pringles     25102
Doritos      22041
Infuzions    12694
Thins        12634
Cobs          9693
Smiths        9572
Tostitos      9471
Twisties      9454
Tyrrells      6442
Grain         6272
Dorito        3183
Cheezels      3149
Name: count, dtype: int64
```

Looking at this, it is evident that Kettle is the clear favourite among other chips.

Deep Dive

```
Deep diving into Mainstream - Young Singles/Couples customer segment for insights
```

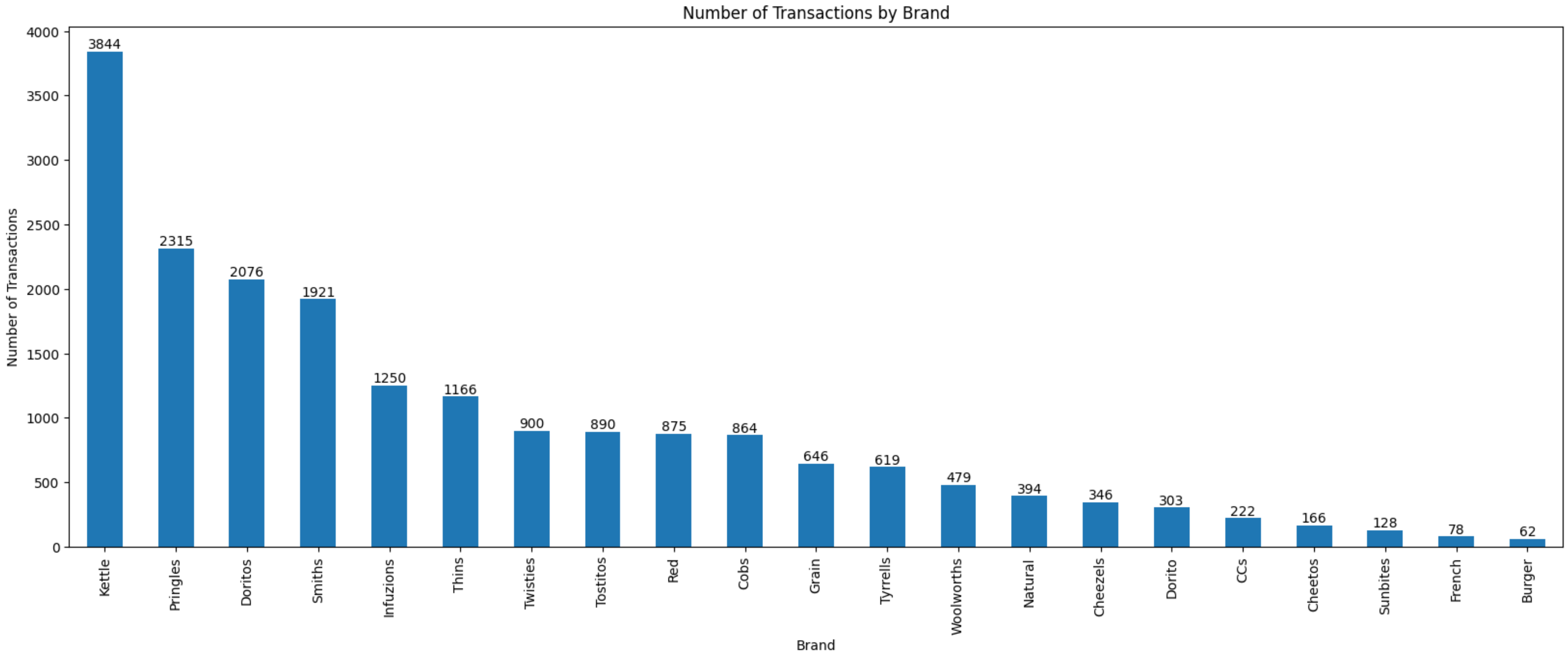
In [ ]:
```
# create a dataframe of only Mainstream - Young Singles/Couples customer segment
data_MS_YSC = data[(data['PREMIUM_CUSTOMER'] == 'Mainstream') & (data['LIFESTAGE'] == 'YOUNG SINGLES/COUPLES')]
data_MS_YSC
```

Out[ ]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	BRAND	
221345	2018-08-16	1	1020	26	19	Smiths Crinkle Cut Snag&Sauce	1	2.6	150	Smiths	SINGL
221346	2018-08-17	1	1163	188	46	Kettle Original	1	5.4	175	Kettle	SINGL
221347	2018-08-14	1	1291	333	27	Woolworths Supreme Cheese Corn Chips	1	1.9	200	Woolworths	SINGL
221348	2019-05-15	3	3031	1227	14	Smiths Crnkle Chip Orgnl Big Bag	1	5.9	380	Smiths	SINGL
221349	2019-05-18	3	3118	1574	62	Pringles Mystery Flavour	1	3.7	134	Pringles	SINGL
...	...	...	...	...	...	...	...	...	...	...	
240884	2018-12-01	272	272377	270186	75	Cobs Popd Sea Salt Chips	2	7.6	110	Cobs	SINGL
240885	2018-07-27	272	272389	270200	114	Kettle Sensations Siracha Lime	2	9.2	150	Kettle	SINGL
240886	2018-11-10	272	272389	270201	26	Pringles Sweet&Spcy BBQ	2	7.4	134	Pringles	SINGL
240887	2019-04-01	272	272389	270202	62	Pringles Mystery Flavour	2	7.4	134	Pringles	SINGL
240888	2018-12-07	272	272391	270205	63	Kettle 135g Swt Pot Sea	2	8.4	135	Kettle	SINGL

19544 rows × 12 columns

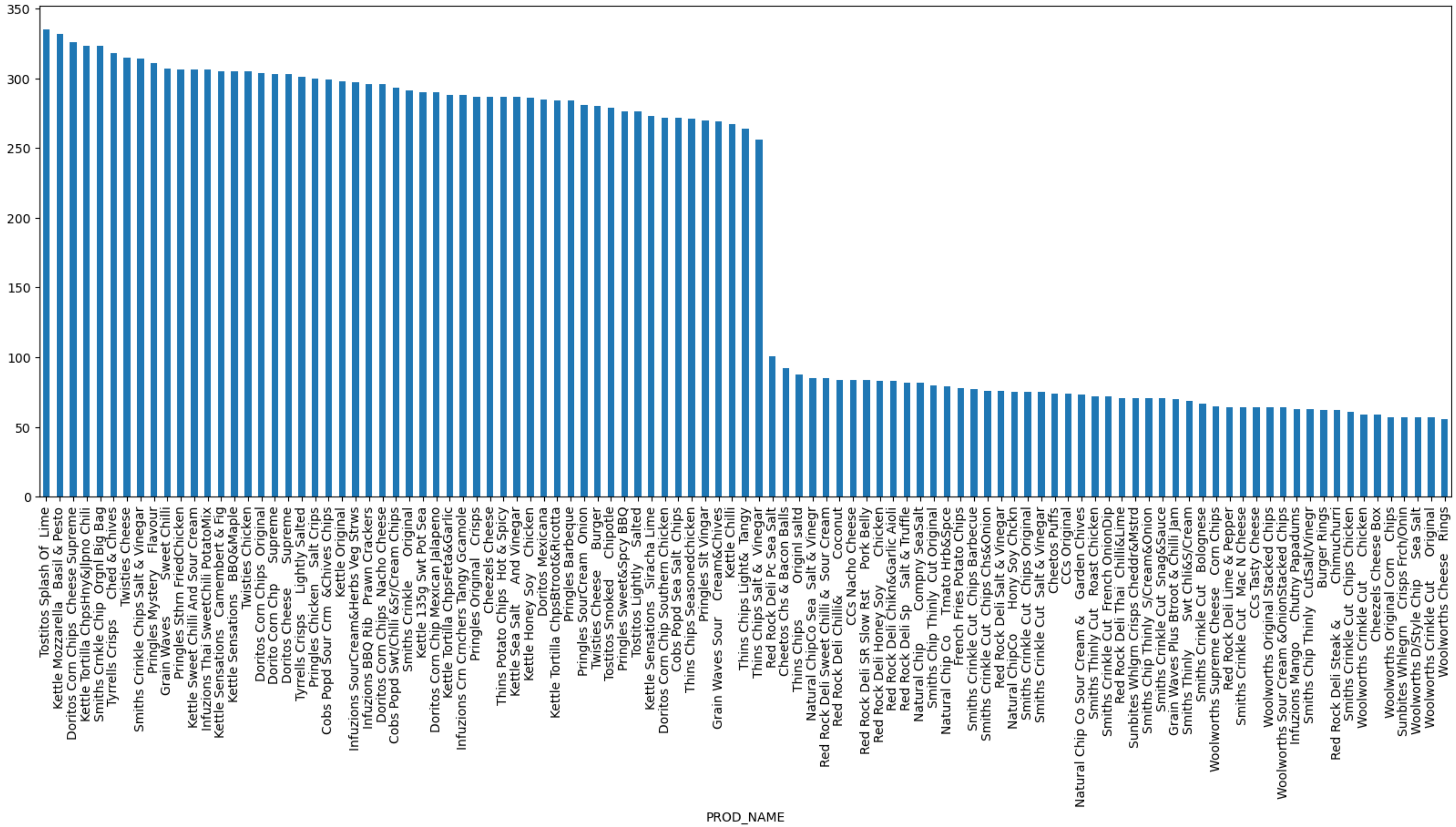
In [ ]:
```
data_MS_YSC.BRAND.value_counts().plot(kind='bar', figsize=(20, 7))
for i in range(len(data_MS_YSC.BRAND.value_counts())):
    plt.text(i, data_MS_YSC.BRAND.value_counts()[i], data_MS_YSC.BRAND.value_counts()[i], ha='center', va='bottom')
plt.xlabel('Brand')
plt.ylabel('Number of Transactions')
plt.title('Number of Transactions by Brand')
plt.show()
```



We can see that Kettle is the favourite brand, significantly higher than other brands.

In [ ]:
```
data_MS_YSC.PROD_NAME.value_counts().plot(kind='bar', figsize=(20, 7))
```

Out[ ]: <Axes: xlabel='PROD_NAME'>



Looking at each product, there is a clear seperation of number of transactions between two sets of products

In [ ]:
```
# all products that have over 250 transactions and its brand
data_MS_YSC[
    data_MS_YSC.PROD_NAME.isin(
```

```
        data_MS_YSC.PROD_NAME.value_counts()[data_MS_YSC.PROD_NAME.value_counts() > 250].index
)].BRAND.value_counts()
```

Out[ ]:

```
BRAND
Kettle       3844
Pringles     2315
Doritos      2076
Infuzions    1187
Thins        1078
Smiths        928
Twisties      900
Tostitos      890
Cobs          864
Tyrrells      619
Grain         576
Dorito        303
Cheezels      287
Name: count, dtype: int64
```

In [ ]:

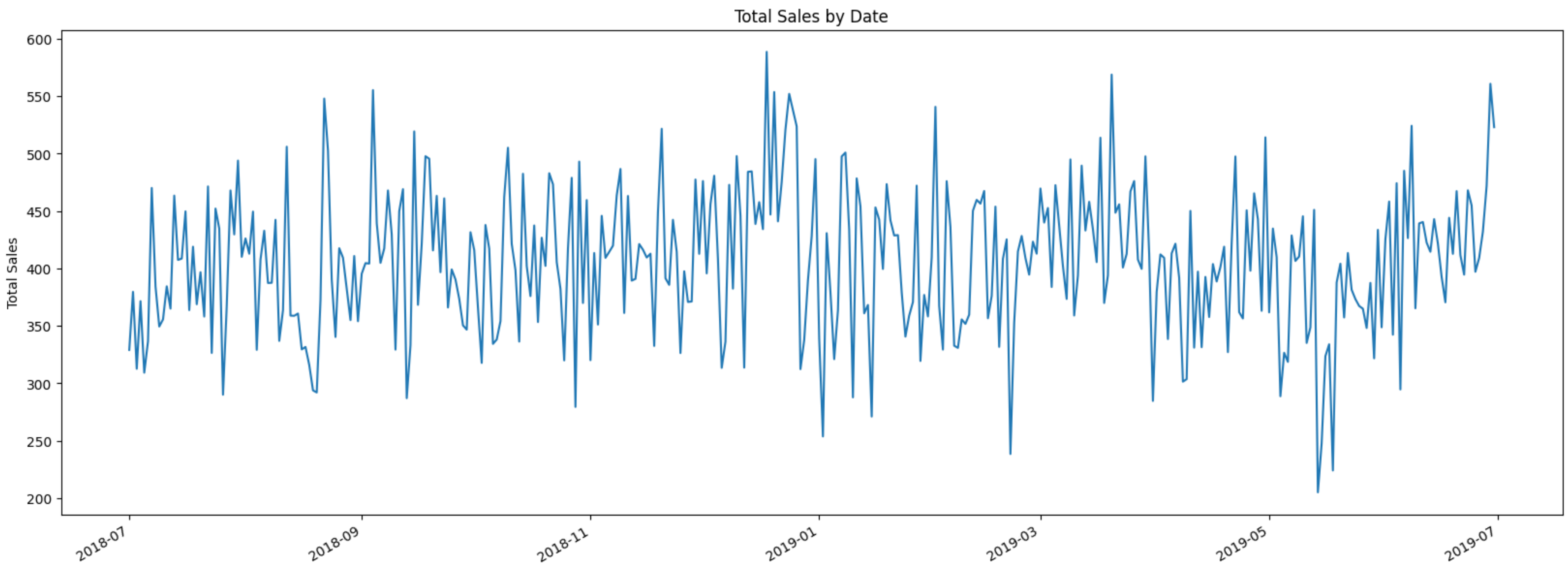
```
data_MS_YSC['PACK_SIZE'].value_counts()
```

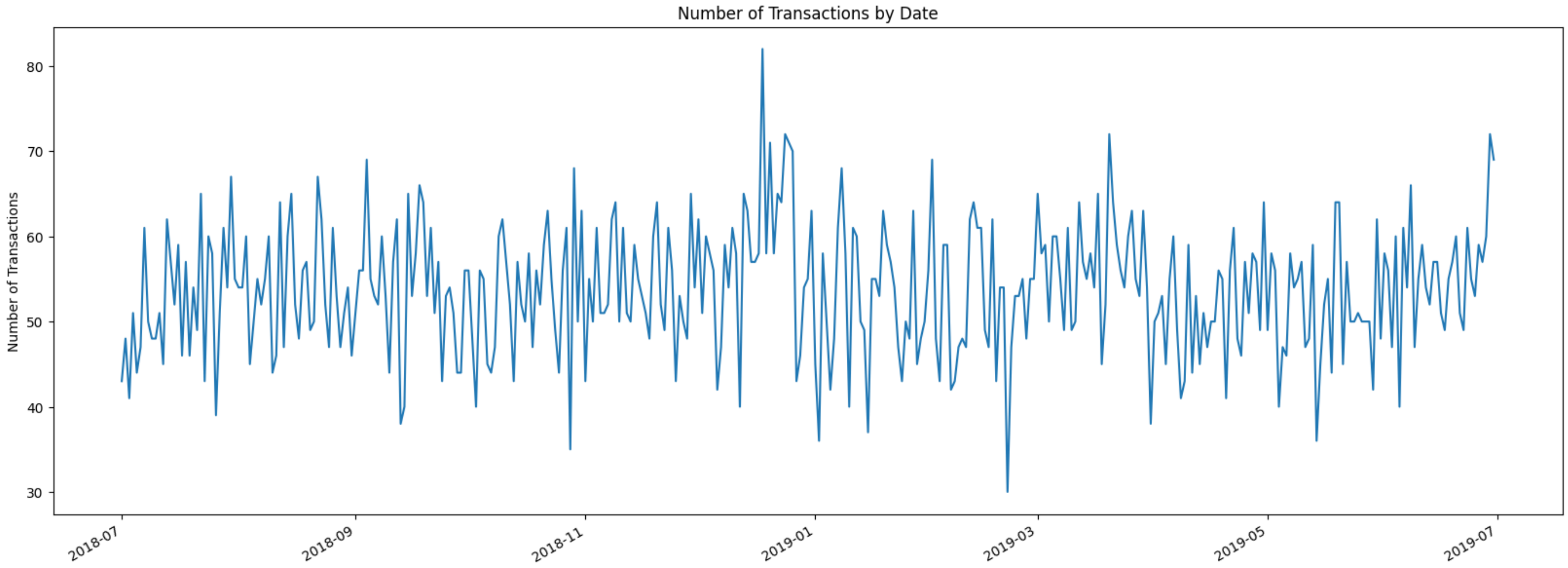
Out[ ]:
```
PACK_SIZE
175    4997
150    3080
134    2315
110    2051
170    1575
330    1195
165    1102
380     626
270     620
210     576
135     290
250     280
200     179
190     148
90      128
160     128
180      70
70       63
220      62
125      59
Name: count, dtype: int64
```

Prefered packsize for this customer segment is 175g, 150g, 134g, 110g, or 170g.

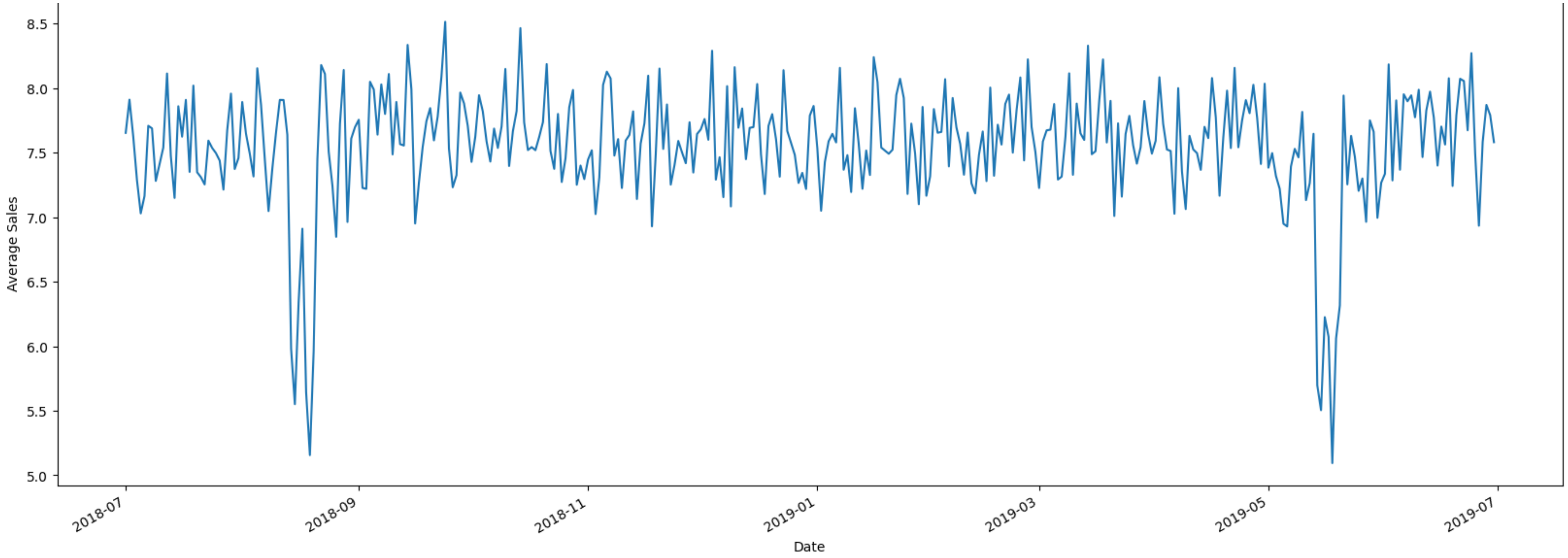
In [ ]:
```
# create a dataframe of total transactions and total sales by date
sales_by_date_MS_YSC = data_MS_YSC.groupby('DATE')[['TOT_SALES','TXN_ID']].agg({'TOT_SALES': 'sum', 'TXN_ID': 'count'})
# create a column of average sales by date
sales_by_date_MS_YSC['AVG_SALES'] = sales_by_date_MS_YSC.TOT_SALES / sales_by_date_MS_YSC.TXN_ID

fig, ax = plt.subplots(3,1,figsize=(20, 25))

# create a plot depicting the total spending of customers over time
data_MS_YSC.groupby('DATE')['TOT_SALES'].sum().plot(ax=ax[0], xlabel='Date', ylabel='Total Sales', title='Total Sales by Date'

# create a plot depicting the number of transactions over time
data_MS_YSC.DATE.value_counts().sort_index().plot(ax=ax[1], xlabel='Date', ylabel='Number of Transactions', title='Number of T

# create a plot depicting the average spending of customers over time
sales_by_date_MS_YSC.AVG_SALES.plot(ax=ax[2], xlabel='Date', ylabel='Average Sales', title='Average Sales by Date')
```

```
plt.show()
```





Average Sales by Date



In [ ]:
```
sales_by_date_MS_YSC.describe()
```

Out[ ]:

	TOT_SALES	TXN_ID	AVG_SALES
count	364.000000	364.000000	364.000000
mean	405.445604	53.692308	7.549323
std	62.240039	7.480284	0.463171
min	205.100000	30.000000	5.094318
25%	361.675000	48.000000	7.352963
50%	408.550000	54.000000	7.586740
75%	448.700000	59.000000	7.826520
max	588.700000	82.000000	8.513953

There are no obvious pattern for the dataset of Mainstream - Young Singles/Couples customer segment other than a rise in Christmas time and two dives in August 2018 and May 2019. In the descriptive statistics, we can say about Mainstream - Young Singles/Couples customer segment that:

- Each customer would spend around 7.5 dollars for chip.
- In total, this customer segment would create a revenue of around 405 dollars for the company.