task2

April 14, 2024

Quantium Data Analytics Virtual Experience Program

0.0.1 Task 2

0.1 Experimentation and uplift testing

Extend your analysis from Task 1 to help you identify benchmark stores that allow you to test the impact of the trial store layouts on customer sales.

Here is the background information on your task

You are part of Quantium's retail analytics team and have been approached by your client, the Category Manager for Chips, has asked us to test the impact of the new trial layouts with a data driven recommendation to whether or not the trial layout should be rolled out to all their stores.

Here is your task

Julia has asked us to evaluate the performance of a store trial which was performed in stores 77, 86 and 88.

To get started use the QVI_data dataset below or your output from task 1 and consider the monthly sales experience of each store.

This can be broken down by: - total sales revenue - total number of customers - average number of transactions per customer

Create a measure to compare different control stores to each of the trial stores to do this write a function to reduce having to re-do the analysis for each trial store. Consider using Pearson correlations or a metric such as a magnitude distance e.g. 1- (Observed distance – minimum distance)/(Maximum distance – minimum distance) as a measure.

Once you have selected your control stores, compare each trial and control pair during the trial period. You want to test if total sales are significantly different in the trial period and if so, check if the driver of change is more purchasing customers or more purchases per customers etc.

[1]:
```
#   Importing the necessary libraries/modules.

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.style as style
import seaborn as sns
import datetime
```

```
import xlrd
%matplotlib inline

#   Ignoring any warnings.

import warnings
warnings.simplefilter(action="ignore", category=FutureWarning)
```

[2]:
```
qvi_data=pd.read_csv("QVI_data.csv")     #   Reading the CSV file into a pandas.
 ↪DataFrame.
qvi_data
```

[2]:
```
        LYLTY_CARD_NBR        DATE  STORE_NBR  TXN_ID  PROD_NBR  \
0                 1000  2018-10-17          1       1         5
1                 1002  2018-09-16          1       2        58
2                 1003  2019-03-07          1       3        52
3                 1003  2019-03-08          1       4       106
4                 1004  2018-11-02          1       5        96
…                    …           …          …     …         …
264829         2370701  2018-12-08         88  240378        24
264830         2370751  2018-10-01         88  240394        60
264831         2370961  2018-10-24         88  240480        70
264832         2370961  2018-10-27         88  240481        65
264833         2373711  2018-12-14         88  241815        16

                                       PROD_NAME  PROD_QTY  TOT_SALES  \
0         Natural Chip        Compny SeaSalt175g         2        6.0
1          Red Rock Deli Chikn&Garlic Aioli 150g         1        2.7
2          Grain Waves Sour    Cream&Chives 210G         1        3.6
3         Natural ChipCo      Hony Soy Chckn175g         1        3.0
4                 WW Original Stacked Chips 160g         1        1.9
…                                            …       …         …
264829     Grain Waves         Sweet Chilli 210g         2        7.2
264830      Kettle Tortilla ChpsFeta&Garlic 150g         2        9.2
264831   Tyrrells Crisps     Lightly Salted 165g         2        8.4
264832   Old El Paso Salsa   Dip Chnky Tom Ht300g        2       10.2
264833  Smiths Crinkle Chips Salt & Vinegar 330g         2       11.4

        PACK_SIZE       BRAND              LIFESTAGE PREMIUM_CUSTOMER
0             175     NATURAL  YOUNG SINGLES/COUPLES          Premium
1             150         RRD  YOUNG SINGLES/COUPLES       Mainstream
2             210     GRNWVES         YOUNG FAMILIES           Budget
3             175     NATURAL         YOUNG FAMILIES           Budget
4             160  WOOLWORTHS  OLDER SINGLES/COUPLES       Mainstream
…             …           …                    …              …
264829        210     GRNWVES         YOUNG FAMILIES       Mainstream
264830        150      KETTLE         YOUNG FAMILIES          Premium
```

```
264831         165     TYRRELLS         OLDER FAMILIES            Budget
264832         300          OLD         OLDER FAMILIES            Budget
264833         330       SMITHS   YOUNG SINGLES/COUPLES       Mainstream

[264834 rows x 12 columns]
```

[3]:
```
qvi_data.info() #    Getting a concise summary of the pandas.DataFrame.
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264834 entries, 0 to 264833
Data columns (total 12 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   LYLTY_CARD_NBR    264834 non-null  int64
 1   DATE              264834 non-null  object
 2   STORE_NBR         264834 non-null  int64
 3   TXN_ID            264834 non-null  int64
 4   PROD_NBR          264834 non-null  int64
 5   PROD_NAME         264834 non-null  object
 6   PROD_QTY          264834 non-null  int64
 7   TOT_SALES         264834 non-null  float64
 8   PACK_SIZE         264834 non-null  int64
 9   BRAND             264834 non-null  object
 10  LIFESTAGE         264834 non-null  object
 11  PREMIUM_CUSTOMER  264834 non-null  object
dtypes: float64(1), int64(6), object(5)
memory usage: 24.2+ MB
```

[4]:
```
qvi_data.isnull().sum() #   Checking for any null values in the pandas.
 ↪DataFrame.
```

[4]:
```
LYLTY_CARD_NBR      0
DATE                0
STORE_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
```

We'll start by assigning a control store to every trial store, which were stores 77, 86 and 88, because we want to find stores that similar attributes to that of the trial stores prior to the entire duration of recorded sales. This way, we can accurately deduce if a particular store has increased its sales during the recorded duration or not.

Firstly, we need to aggregate some statistics about the stores for each recorded month over the entire duration of sales. We can start by finding the total sales for each month during the entire recorded duration, for each store.

[5]:
```
qvi_data["YEAR_MONTH"]=pd.to_datetime(qvi_data["DATE"]).dt.to_period("M")   # ␣
↪Storing the year and month of the recorded duration in a separate column.
qvi_data
```

[5]:
```
        LYLTY_CARD_NBR        DATE  STORE_NBR  TXN_ID  PROD_NBR  \
0                 1000  2018-10-17          1       1         5
1                 1002  2018-09-16          1       2        58
2                 1003  2019-03-07          1       3        52
3                 1003  2019-03-08          1       4       106
4                 1004  2018-11-02          1       5        96
…                  …           …         …       …       …
264829         2370701  2018-12-08         88  240378        24
264830         2370751  2018-10-01         88  240394        60
264831         2370961  2018-10-24         88  240480        70
264832         2370961  2018-10-27         88  240481        65
264833         2373711  2018-12-14         88  241815        16

                                       PROD_NAME  PROD_QTY  TOT_SALES  \
0         Natural Chip        Compny SeaSalt175g         2        6.0
1          Red Rock Deli Chikn&Garlic Aioli 150g         1        2.7
2          Grain Waves Sour    Cream&Chives 210G         1        3.6
3         Natural ChipCo      Hony Soy Chckn175g         1        3.0
4                 WW Original Stacked Chips 160g         1        1.9
…                                            …       …        …
264829     Grain Waves         Sweet Chilli 210g         2        7.2
264830      Kettle Tortilla ChpsFeta&Garlic 150g         2        9.2
264831    Tyrrells Crisps     Lightly Salted 165g         2        8.4
264832    Old El Paso Salsa   Dip Chnky Tom Ht300g         2       10.2
264833    Smiths Crinkle Chips Salt & Vinegar 330g         2       11.4

        PACK_SIZE       BRAND              LIFESTAGE PREMIUM_CUSTOMER  \
0             175     NATURAL  YOUNG SINGLES/COUPLES          Premium
1             150         RRD  YOUNG SINGLES/COUPLES       Mainstream
2             210    GRNWVES          YOUNG FAMILIES           Budget
3             175     NATURAL         YOUNG FAMILIES           Budget
4             160  WOOLWORTHS  OLDER SINGLES/COUPLES       Mainstream
…            …          …                    …                …
264829        210     GRNWVES         YOUNG FAMILIES       Mainstream
264830        150      KETTLE         YOUNG FAMILIES          Premium
264831        165    TYRRELLS         OLDER FAMILIES           Budget
264832        300         OLD         OLDER FAMILIES           Budget
264833        330      SMITHS  YOUNG SINGLES/COUPLES       Mainstream
```

```
       YEAR_MONTH
0         2018-10
1         2018-09
2         2019-03
3         2019-03
4         2018-11
…           …
264829    2018-12
264830    2018-10
264831    2018-10
264832    2018-10
264833    2018-12

[264834 rows x 13 columns]
```

[6]:

```
total_sales=qvi_data.groupby(["STORE_NBR", "YEAR_MONTH"])["TOT_SALES"].sum()   #   Grouping the pandas.DataFrame by the STORE_NBR and YEAR_MONTH column, and summing up the total sales for them.
total_sales=total_sales.to_frame()  #   Converting the pandas.Series to a pandas.DataFrame.
total_sales
```

[6]:

```
                      TOT_SALES
STORE_NBR YEAR_MONTH
1         2018-07         206.9
          2018-08         176.1
          2018-09         278.8
          2018-10         188.1
          2018-11         192.6
…                           …
272       2019-02         395.5
          2019-03         442.3
          2019-04         445.1
          2019-05         314.6
          2019-06         312.1

[3169 rows x 1 columns]
```

Likewise, we can also count the number of unique customers for for each month during the entire recorded duration, for each store.

[7]:

```
total_customers=qvi_data.groupby(["STORE_NBR", "YEAR_MONTH"])["LYLTY_CARD_NBR"].nunique()   #   Grouping the pandas.DataFrame by the STORE_NBR and YEAR_MONTH column, and counting the unique number of customers for them.
total_customers=total_customers.to_frame()  #   Converting the pandas.Series to a pandas.DataFrame.
```

```
total_customers
```

[7]:

```
                      LYLTY_CARD_NBR
STORE_NBR YEAR_MONTH
1         2018-07                 49
          2018-08                 42
          2018-09                 59
          2018-10                 44
          2018-11                 46
…                                …
272       2019-02                 45
          2019-03                 50
          2019-04                 54
          2019-05                 34
          2019-06                 34

[3169 rows x 1 columns]
```

Additionally, we can also find the number of transactions per customer for each recorded month by diving the count of the number of unique transactions and the count of the number of unique customers for each store.

[8]:

```
transactions_per_customer=qvi_data.groupby(["STORE_NBR",␣
↪"YEAR_MONTH"])["TXN_ID"].nunique()/qvi_data.groupby(["STORE_NBR",␣
↪"YEAR_MONTH"])["LYLTY_CARD_NBR"].nunique()   #   Grouping the pandas.
↪DataFrame by the STORE_NBR and YEAR_MONTH column, and counting the unique␣
↪number of transactions per customer for them.
transactions_per_customer=transactions_per_customer.to_frame()  #   Converting␣
↪the pandas.Series to a pandas.DataFrame.
transactions_per_customer
```

[8]:

```
                             0
STORE_NBR YEAR_MONTH
1         2018-07     1.061224
          2018-08     1.023810
          2018-09     1.050847
          2018-10     1.022727
          2018-11     1.021739
…                          …
272       2019-02     1.066667
          2019-03     1.060000
          2019-04     1.018519
          2019-05     1.176471
          2019-06     1.088235

[3169 rows x 1 columns]
```

```
[9]: dataframe_list=[total_sales, total_customers, transactions_per_customer]    # 
     ↪Creating a list of all the pandas.DataFrames.
     dataframe=pd.concat(dataframe_list, axis=1) #   Concatenating all the pandas.
     ↪DataFrames into one.
     dataframe.columns=["TOT_SALES", "TOT_CUST", "TXN_PER_CUST"] #   Renaming the
     ↪columns of the pandas.DataFrame.
     dataframe
```

```
[9]:                       TOT_SALES  TOT_CUST  TXN_PER_CUST
     STORE_NBR YEAR_MONTH
     1         2018-07         206.9        49      1.061224
               2018-08         176.1        42      1.023810
               2018-09         278.8        59      1.050847
               2018-10         188.1        44      1.022727
               2018-11         192.6        46      1.021739
     …                             …       …             …
     272       2019-02         395.5        45      1.066667
               2019-03         442.3        50      1.060000
               2019-04         445.1        54      1.018519
               2019-05         314.6        34      1.176471
               2019-06         312.1        34      1.088235

     [3169 rows x 3 columns]
```

```
[10]: dataframe.isnull().sum() #   Checking for any null values in the pandas.
      ↪DataFrame.
```

```
[10]: TOT_SALES       0
      TOT_CUST        0
      TXN_PER_CUST    0
      dtype: int64
```

Since the dataset contains transaction details of many stores, there may be some stores that did not record sales for the entire duration.

```
[11]: recorded_stores=pd.pivot_table(qvi_data, index="STORE_NBR",
      ↪columns="YEAR_MONTH", values="TXN_ID", aggfunc="count") #   Pivoting the
      ↪pandas.DataFrame to get all the recorded transactions for each store during
      ↪the entire duration.
      recorded_stores
```

```
[11]: YEAR_MONTH  2018-07  2018-08  2018-09  2018-10  2018-11  2018-12  2019-01  \
      STORE_NBR
      1              52.0     43.0     62.0     45.0     47.0     47.0     36.0
      2              41.0     43.0     37.0     43.0     40.0     38.0     45.0
      3             138.0    134.0    119.0    119.0    118.0    129.0    121.0
      4             160.0    151.0    138.0    155.0    139.0    133.0    168.0
```

```
5             120.0    112.0    125.0    107.0    111.0    125.0    118.0
…                 …        …        …        …        …        …        …
268            52.0     54.0     34.0     48.0     51.0     43.0     38.0
269           139.0    132.0    124.0    148.0    136.0    133.0    144.0
270           139.0    154.0    126.0    119.0    133.0    149.0    155.0
271           129.0    101.0    114.0    114.0    122.0    117.0    120.0
272            52.0     48.0     36.0     51.0     45.0     47.0     50.0

YEAR_MONTH  2019-02  2019-03  2019-04  2019-05  2019-06
STORE_NBR
1              55.0     49.0     43.0     51.0     43.0
2              32.0     46.0     49.0     50.0     42.0
3             139.0    130.0    110.0    123.0    122.0
4             102.0    135.0    137.0    126.0    134.0
5             106.0     97.0    109.0    104.0    127.0
…                 …        …        …        …        …
268            37.0     47.0     50.0     52.0     40.0
269           133.0    122.0    139.0    130.0    127.0
270           125.0    143.0    132.0    128.0    127.0
271           102.0    101.0    109.0    127.0    129.0
272            48.0     53.0     56.0     40.0     37.0

[272 rows x 12 columns]
```

[12]:
```
recorded_stores.isnull().sum()   #   Checking for any null values in the pandas.
 ↪DataFrame.
```

[12]:
```
YEAR_MONTH
2018-07    6
2018-08    9
2018-09    8
2018-10    7
2018-11    8
2018-12    9
2019-01    9
2019-02    8
2019-03    7
2019-04    7
2019-05    9
2019-06    8
Freq: M, dtype: int64
```

As we can see, there are null values for a few months, which means that some of these are unrecorded for certain stores, so we need to find them and remove these stores from the dataset, since they can't be control stores anyway.

[13]:
```python
unrecorded_stores=[]
for i in recorded_stores.index:
    if recorded_stores.loc[i].isnull().any():
        unrecorded_stores.append(i)
unrecorded_stores
```

[13]: [11, 31, 44, 76, 85, 92, 117, 193, 206, 211, 218, 252]

[14]:
```python
dataframe=dataframe.drop(unrecorded_stores, axis=0)
dataframe
```

[14]:
```
                     TOT_SALES  TOT_CUST  TXN_PER_CUST
STORE_NBR YEAR_MONTH
1         2018-07        206.9        49      1.061224
          2018-08        176.1        42      1.023810
          2018-09        278.8        59      1.050847
          2018-10        188.1        44      1.022727
          2018-11        192.6        46      1.021739
…                          …        …            …
272       2019-02        395.5        45      1.066667
          2019-03        442.3        50      1.060000
          2019-04        445.1        54      1.018519
          2019-05        314.6        34      1.176471
          2019-06        312.1        34      1.088235

[3120 rows x 3 columns]
```

We can filter the dataset to the pre-trial duration — that is, before February 2022.

[15]:
```python
pre_trial_data=dataframe.loc[dataframe.index.
 ↪get_level_values("YEAR_MONTH")<"2019-02"]  #   Extracting the pandas.
 ↪DataFrame for the pre-trial duration.
pre_trial_data=pre_trial_data.reset_index()
pre_trial_data
```

[15]:
```
      STORE_NBR YEAR_MONTH  TOT_SALES  TOT_CUST  TXN_PER_CUST
0             1    2018-07      206.9        49      1.061224
1             1    2018-08      176.1        42      1.023810
2             1    2018-09      278.8        59      1.050847
3             1    2018-10      188.1        44      1.022727
4             1    2018-11      192.6        46      1.021739
…           …        …        …         …            …
1815        272    2018-09      304.7        32      1.125000
1816        272    2018-10      430.6        44      1.136364
1817        272    2018-11      376.2        41      1.097561
1818        272    2018-12      403.9        47      1.000000
1819        272    2019-01      423.0        46      1.086957
```

```
[1820 rows x 5 columns]
```

From the pre-trial dataset, we can now filter the control stores, which are the ones that do *not* include STORE_NBR 77, 88, and 89.

[16]:
```
control_stores=pre_trial_data[(pre_trial_data.STORE_NBR!=77 ) & (pre_trial_data.
 ↪STORE_NBR!=86) & (pre_trial_data.STORE_NBR!=88)][["TOT_SALES", "TOT_CUST",␣
 ↪"TXN_PER_CUST"]].groupby(pre_trial_data.STORE_NBR).sum()
control_stores
```

[16]:
```
           TOT_SALES  TOT_CUST  TXN_PER_CUST
STORE_NBR
1            1386.90       317      7.327967
2            1128.50       272      7.359700
3            7526.15       744      8.209829
4            9127.00       849      8.535253
5            5739.70       651      8.791906
…                …         …             …
268          1549.05       304      7.373037
269          6664.50       746      8.921035
270          6697.95       734      9.147187
271          5765.10       652      8.671966
272          2744.35       302      7.620124

[257 rows x 3 columns]
```

Likewise, we can also filter the trial stores from the dataset.

[17]:
```
trial_stores=pre_trial_data[(pre_trial_data.STORE_NBR==77 ) | (pre_trial_data.
 ↪STORE_NBR==86) | (pre_trial_data.STORE_NBR==88)][["TOT_SALES", "TOT_CUST",␣
 ↪"TXN_PER_CUST"]].groupby(pre_trial_data.STORE_NBR).sum()
trial_stores
```

[17]:
```
           TOT_SALES  TOT_CUST  TXN_PER_CUST
STORE_NBR
77           1699.00       299      7.405289
86           6119.85       697      8.798544
88           9383.60       880      8.523817
```

With both the control stores and the trial stores filtered, we can find the Pearson correlation coefficient of the attributes between the two to find the control stores for each of the trial stores.

- **STORE_NBR 77:**

[18]:

```
difference=control_stores.loc[control_stores.corrwith(trial_stores.loc[77],␣
↪method="pearson", axis=1).nlargest(5).index]     #   Getting the pandas.
↪DataFrame for the top five stores with the highest correlation with the␣
↪trial store.

#   Getting the difference between the trial store and the top five stores with␣
↪the highest correlation with the trial store.

difference=(trial_stores.loc[77]-difference).sort_values(by="TOT_SALES",␣
↪ascending=False)
difference["DIFFERENCE"]=difference["TOT_SALES"]-difference["TOT_SALES"].mean()
difference.sort_values(by="DIFFERENCE", ascending=False)     #   Sorting the␣
↪pandas.DataFrame by the DIFFERENCE column.
```

[18]:

STORE_NBR	TOT_SALES	TOT_CUST	TXN_PER_CUST	DIFFERENCE
139	1493.2	257.0	0.405289	609.34
135	1486.9	256.0	0.012432	603.04
161	1459.0	252.0	0.405289	575.14
233	39.2	1.0	0.115969	-844.66
46	-59.0	-3.0	0.094215	-942.86

For STORE_NBR 77, we can see that STORE_NBR 46 would be the most suitable control store.

- **STORE_NBR 86:**

[19]:
```
difference=control_stores.loc[control_stores.corrwith(trial_stores.loc[86],␣
↪axis=1).nlargest(5).index]   #   Getting the pandas.DataFrame for the top␣
↪five stores with the highest correlation with the trial store.

#   Getting the difference between the trial store and the top five stores with␣
↪the highest correlation with the trial store.

difference=(trial_stores.loc[86]-difference).sort_values(by="TOT_SALES",␣
↪ascending=False)
difference["DIFFERENCE"]=difference["TOT_SALES"]-difference["TOT_SALES"].mean()
difference.sort_values(by="DIFFERENCE", ascending=False)     #   Sorting the␣
↪pandas.DataFrame by the DIFFERENCE column.
```

[19]:

STORE_NBR	TOT_SALES	TOT_CUST	TXN_PER_CUST	DIFFERENCE
258	5934.85	670.0	1.798544	4066.46
215	3411.85	386.0	1.486773	1543.46
225	29.25	3.0	0.023669	-1839.14
196	-6.45	1.0	0.040716	-1874.84
57	-27.55	-2.0	0.031815	-1895.94

For STORE_NBR 86, we can see that STORE_NBR 57 would be the most suitable control store.

- **STORE_NBR 88:**

[20]:
```python
difference=control_stores.loc[control_stores.corrwith(trial_stores.loc[88],␣
 ↪axis=1).nlargest(5).index]  #   Getting the pandas.DataFrame for the top␣
 ↪five stores with the highest correlation with the trial store.

#   Getting the difference between the trial store and the top five stores with␣
 ↪the highest correlation with the trial store.

difference=(trial_stores.loc[88]-difference).sort_values(by="TOT_SALES",␣
 ↪ascending=False)
difference["DIFFERENCE"]=difference["TOT_SALES"]-difference["TOT_SALES"].mean()
difference.sort_values(by="DIFFERENCE", ascending=False)     #   Sorting the␣
 ↪pandas.DataFrame by the DIFFERENCE column.
```

[20]:

STORE_NBR	TOT_SALES	TOT_CUST	TXN_PER_CUST	DIFFERENCE
60	1697.1	154.0	0.052504	783.5
75	1420.1	129.0	0.078986	506.5
72	865.1	79.0	0.085871	-48.5
203	439.9	38.0	0.135139	-473.7
165	145.8	18.0	0.093389	-767.8

For STORE_NBR 88, we can see that STORE_NBR 165 would be the most suitable control store.

Let's compare the different control stores to each of the trial stores during the pre-trial duration to find any significant difference in the statistics.

[21]:
```python
#   Extracting the pandas.DataFrames for each of the trial stores.

trial_stores_one=pre_trial_data.loc[pre_trial_data.STORE_NBR.isin([77])].
 ↪reset_index()
trial_stores_two=pre_trial_data.loc[pre_trial_data.STORE_NBR.isin([86])].
 ↪reset_index()
trial_stores_three=pre_trial_data.loc[pre_trial_data.STORE_NBR.isin([88])].
 ↪reset_index()
```

[22]:
```python
#   Extracting the pandas.DataFrames for each of the control stores.

control_stores_one=pre_trial_data.loc[pre_trial_data.STORE_NBR.isin([46])].
 ↪reset_index()
control_stores_two=pre_trial_data.loc[pre_trial_data.STORE_NBR.isin([57])].
 ↪reset_index()
control_stores_three=pre_trial_data.loc[pre_trial_data.STORE_NBR.isin([165])].
 ↪reset_index()
```

[23]:

```
stores=pd.concat([trial_stores_one, trial_stores_two, trial_stores_three,␣
↪control_stores_one, control_stores_two, control_stores_three], axis=0)    # ␣
↪Concatenating all the pandas.DataFrames into one.
stores
```

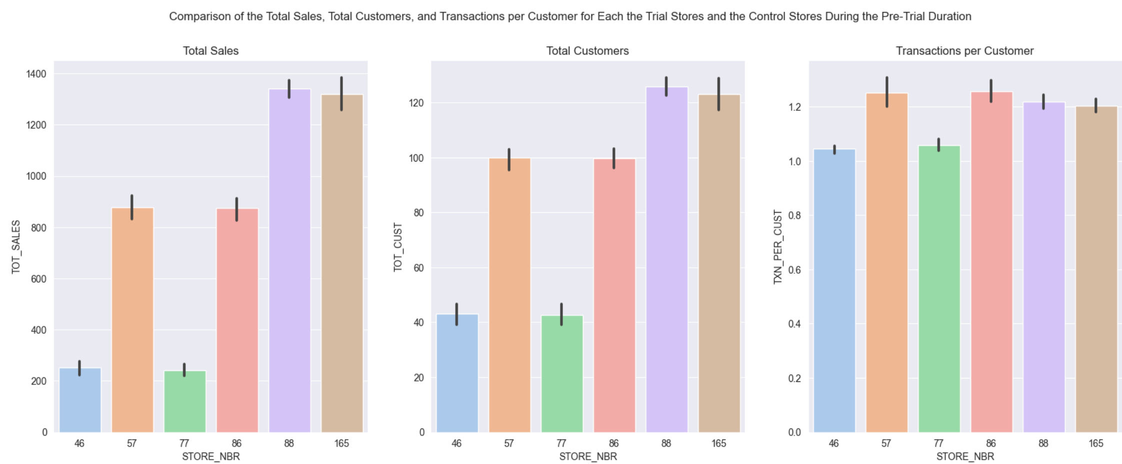
[23]:

	index	STORE_NBR	YEAR_MONTH	TOT_SALES	TOT_CUST	TXN_PER_CUST
0	504	77	2018-07	296.80	51	1.078431
1	505	77	2018-08	255.50	47	1.021277
2	506	77	2018-09	225.20	42	1.047619
3	507	77	2018-10	204.50	37	1.027027
4	508	77	2018-11	245.30	41	1.073171
5	509	77	2018-12	267.30	46	1.043478
6	510	77	2019-01	204.40	35	1.114286
0	560	86	2018-07	892.20	99	1.272727
1	561	86	2018-08	764.05	94	1.170213
2	562	86	2018-09	914.60	103	1.242718
3	563	86	2018-10	948.40	109	1.266055
4	564	86	2018-11	918.00	100	1.250000
5	565	86	2018-12	841.20	98	1.224490
6	566	86	2019-01	841.40	94	1.372340
0	574	88	2018-07	1310.00	129	1.186047
1	575	88	2018-08	1323.80	131	1.206107
2	576	88	2018-09	1423.00	124	1.266129
3	577	88	2018-10	1352.40	123	1.260163
4	578	88	2018-11	1382.80	130	1.200000
5	579	88	2018-12	1325.20	126	1.174603
6	580	88	2019-01	1266.40	117	1.230769
0	294	46	2018-07	253.00	45	1.066667
1	295	46	2018-08	240.70	44	1.045455
2	296	46	2018-09	233.00	41	1.048780
3	297	46	2018-10	275.10	47	1.042553
4	298	46	2018-11	273.10	42	1.047619
5	299	46	2018-12	306.90	50	1.060000
6	300	46	2019-01	176.20	33	1.000000
0	371	57	2018-07	839.60	103	1.203883
1	372	57	2018-08	915.40	102	1.274510
2	373	57	2018-09	792.80	99	1.171717
3	374	57	2018-10	965.80	104	1.307692
4	375	57	2018-11	830.00	100	1.170000
5	376	57	2018-12	951.00	104	1.259615
6	377	57	2019-01	852.80	87	1.379310
0	1099	165	2018-07	1457.00	133	1.255639
1	1100	165	2018-08	1206.60	109	1.256881
2	1101	165	2018-09	1281.20	122	1.172131
3	1102	165	2018-10	1234.40	118	1.169492
4	1103	165	2018-11	1291.20	126	1.166667
5	1104	165	2018-12	1345.40	121	1.206612

```
6   1105         165     2019-01     1422.00        133       1.203008
```

[24]:
```
#   Plotting the bar graphs for the total sales, total customers, and
 ↪transactions per customer for each of the trial stores and the control
 ↪stores.

sns.set_style("darkgrid")
figure, axis=plt.subplots(1, 3, figsize=(20, 7))
sns.barplot(x="STORE_NBR", y="TOT_SALES", data=stores, ax=axis[0],
 ↪palette="pastel")
axis[0].set_title("Total Sales")
sns.barplot(x="STORE_NBR", y="TOT_CUST", data=stores, ax=axis[1],
 ↪palette="pastel")
axis[1].set_title("Total Customers")
sns.barplot(x="STORE_NBR", y="TXN_PER_CUST", data=stores, ax=axis[2],
 ↪palette="pastel")
axis[2].set_title("Transactions per Customer")
figure.suptitle("Comparison of the Total Sales, Total Customers, and
 ↪Transactions per Customer for Each the Trial Stores and the Control Stores
 ↪During the Pre-Trial Duration")
plt.show()
```



While the other trial stores performed the same as their corresponding control stores, we can see, however, that STORE_NBR 88 slightly out-performed its control store in all attributes. We can also notice that STORE_NBR 86 and 88 show a significant difference in terms of the total sales, but this isn't the case with STORE_NBR 77, whose sales are considerably less.

Likewise, we can also compare different control stores to each of the trial stores during the trial duration, as well, to find if the total sales are significantly different in the trial duration.

[25]:
```python
trial_data=dataframe.loc[dataframe.index.
    ↪get_level_values("YEAR_MONTH")>="2019-02"]   #   Extracting the pandas.
    ↪DataFrame for the trial duration.
trial_data=trial_data.reset_index()
trial_data
```

[25]:
```
      STORE_NBR YEAR_MONTH  TOT_SALES  TOT_CUST  TXN_PER_CUST
0             1    2019-02      225.4        52      1.057692
1             1    2019-03      192.9        45      1.088889
2             1    2019-04      192.9        42      1.023810
3             1    2019-05      221.4        46      1.108696
4             1    2019-06      174.1        42      1.000000
…           …          …        …          …         …
1295        272    2019-02      395.5        45      1.066667
1296        272    2019-03      442.3        50      1.060000
1297        272    2019-04      445.1        54      1.018519
1298        272    2019-05      314.6        34      1.176471
1299        272    2019-06      312.1        34      1.088235

[1300 rows x 5 columns]
```

[26]:
```python
#   Extracting the pandas.DataFrames for each of the trial stores.

trial_stores_one=trial_data.loc[trial_data.STORE_NBR.isin([77])].reset_index()
trial_stores_two=trial_data.loc[trial_data.STORE_NBR.isin([86])].reset_index()
trial_stores_three=trial_data.loc[trial_data.STORE_NBR.isin([88])].reset_index()
```

[27]:
```python
#   Extracting the pandas.DataFrames for each of the control stores.

control_stores_one=trial_data.loc[trial_data.STORE_NBR.isin([46])].reset_index()
control_stores_two=trial_data.loc[trial_data.STORE_NBR.isin([57])].reset_index()
control_stores_three=trial_data.loc[trial_data.STORE_NBR.isin([165])].
    ↪reset_index()
```

[28]:
```python
stores=pd.concat([trial_stores_one, trial_stores_two, trial_stores_three,␣
    ↪control_stores_one, control_stores_two, control_stores_three], axis=0)    #␣
    ↪ Concatenating all the pandas.DataFrames into one.
stores
```

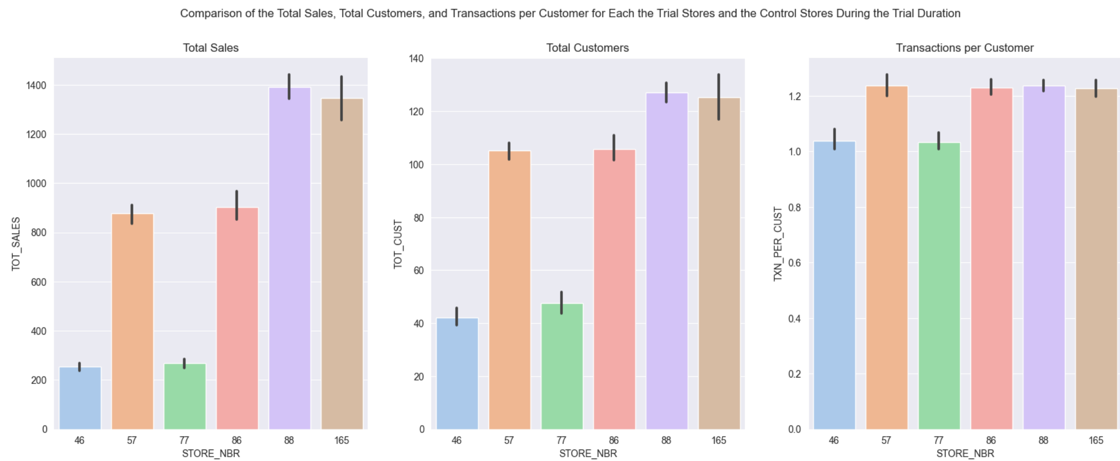
[28]:
```
   index  STORE_NBR YEAR_MONTH  TOT_SALES  TOT_CUST  TXN_PER_CUST
0    360         77    2019-02     235.00        45      1.000000
1    361         77    2019-03     278.50        50      1.100000
2    362         77    2019-04     263.50        47      1.021277
3    363         77    2019-05     299.30        55      1.018182
4    364         77    2019-06     264.70        41      1.024390
0    400         86    2019-02     913.20       107      1.289720
1    401         86    2019-03    1026.80       115      1.217391
```

```
2   402   86  2019-04   848.20  105  1.200000
3   403   86  2019-05   889.30  104  1.230769
4   404   86  2019-06   838.00   98  1.204082
0   410   88  2019-02  1370.20  124  1.233871
1   411   88  2019-03  1477.20  134  1.261194
2   412   88  2019-04  1439.40  128  1.265625
3   413   88  2019-05  1308.25  128  1.203125
4   414   88  2019-06  1354.60  121  1.223140
0   210   46  2019-02   222.40   38  1.000000
1   211   46  2019-03   259.20   41  1.000000
2   212   46  2019-04   260.00   47  1.042553
3   213   46  2019-05   243.55   38  1.105263
4   214   46  2019-06   280.30   47  1.042553
0   265   57  2019-02   919.80  108  1.194444
1   266   57  2019-03   807.40   99  1.222222
2   267   57  2019-04   900.00  106  1.292453
3   268   57  2019-05   846.70  109  1.192661
4   269   57  2019-06   911.00  104  1.288462
0   785  165  2019-02  1237.50  113  1.230088
1   786  165  2019-03  1215.40  114  1.184211
2   787  165  2019-04  1391.70  129  1.232558
3   788  165  2019-05  1441.05  133  1.285714
4   789  165  2019-06  1450.30  137  1.197080
```

[29]:

```
#  Plotting the bar graphs for the total sales, total customers, and␣
↪transactions per customer for each of the trial stores and the control␣
↪stores.

sns.set_style("darkgrid")
figure, axis=plt.subplots(1, 3, figsize=(20, 7))
sns.barplot(x="STORE_NBR", y="TOT_SALES", data=stores, ax=axis[0],␣
↪palette="pastel")
axis[0].set_title("Total Sales")
sns.barplot(x="STORE_NBR", y="TOT_CUST", data=stores, ax=axis[1],␣
↪palette="pastel")
axis[1].set_title("Total Customers")
sns.barplot(x="STORE_NBR", y="TXN_PER_CUST", data=stores, ax=axis[2],␣
↪palette="pastel")
axis[2].set_title("Transactions per Customer")
figure.suptitle("Comparison of the Total Sales, Total Customers, and␣
↪Transactions per Customer for Each the Trial Stores and the Control Stores␣
↪During the Trial Duration")
plt.show()
```



We can, once again, notice that STORE_NBR 88 slightly out-performs its control store, STORE_NBR 165, and still remains the best implementation of the trial of all the trial stores. The driver for this seems to be the purchasing customers rather than purchases per customer, as we can see that with the increase in the total customers, there's also an increase in the total sales almost identically, but the transactions per customer seem to be reasonably high for all the trial stores regardless of the total sales.

0.1.1 Conclusion:

- While the other trial stores performed the same as their corresponding control stores, we can see, however, that STORE_NBR 88 slightly out-performed its control store, STORE_NBR 165, in all attributes.
- STORE_NBR 86 and 88 show a significant difference in terms of the total sales, but this isn't the case with STORE_NBR 77, which may be because of the way the trial was implemented for it.
- Due to the maximum difference in the total sales of all the trial stores, STORE_NBR 88 remains the best implementation of the trial.
- The driver for the increase in total sales seems to be the purchasing customers rather than purchases per customer — the more the customers, the higher the sales.