task-2

January 25, 2024

Quantium Data Analytics Virtual Experience Program - Task 2

Exploration of Experimentation and Uplift Testing

Expanding on the analysis conducted in Task 1 to identify benchmark stores for assessing the impact of the trial store layouts on customer sales.

Background:

As a member of Quantium's retail analytics team, you have received a request from the Category Manager for Chips. The manager is interested in testing the effects of new trial layouts and seeks a data-driven recommendation on whether to implement these layouts across all stores.

Task Overview:

Julia, the Category Manager, has tasked the team with evaluating the performance of a store trial conducted in stores 77, 86, and 88. Utilize the QVI_data dataset provided below or the output from Task 1, focusing on the monthly sales experience of each store. Break down the analysis into:

Total sales revenue Total number of customers Average number of transactions per customer Create a standardized measure to compare different control stores with each trial store. To streamline the analysis for each trial store, consider implementing a function. This function may utilize Pearson correlations or a metric like magnitude distance (e.g., 1 - (Observed distance – minimum distance) / (Maximum distance – minimum distance)).

Once control stores are identified, compare each trial and control pair during the trial period. The goal is to determine if total sales exhibit significant differences during the trial period. If differences are observed, investigate whether the driver of change is an increase in purchasing customers, purchases per customer, or other factors.

[1]:
```
# Importing required 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

# Suppressing warnings.
```

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

[2]:
```python
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]:
```
# Displaying a concise summary of the pandas DataFrame.
qvi_data.info()
```

```
<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]:
```
# Checking for null values in the pandas DataFrame and displaying the sum of␣
↪null values for each column.
qvi_data.isnull().sum()
```

[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
```

Let's initiate the process by matching a control store with each trial store, specifically stores 77, 86, and 88. The objective is to identify stores with similar characteristics to the trial stores before the entire sales recording period. This approach enables us to precisely determine whether a specific store has experienced a sales increase throughout the recorded duration.

To begin, we must aggregate key statistics about the stores for each recorded month across the entire sales duration. Our initial focus is on determining the total sales for each store in each month throughout the complete recording period.

[6]:
```python
# Create a new column "YEAR_MONTH" to store the year and month of the recorded␣
↪duration
qvi_data["YEAR_MONTH"] = pd.to_datetime(qvi_data["DATE"]).dt.to_period("M")

# Display the updated pandas DataFrame
qvi_data
```

[6]:
```
        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]
```

[7]:
```python
# Group the pandas DataFrame by "STORE_NBR" and "YEAR_MONTH" columns, and sum␣
↪up the total sales for each group
total_sales = qvi_data.groupby(["STORE_NBR", "YEAR_MONTH"])["TOT_SALES"].sum()

# Convert the pandas Series to a pandas DataFrame
total_sales = total_sales.to_frame()

# Display the updated pandas DataFrame
total_sales
```

[7]:
```
                      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]
```

Similarly, we can determine the count of unique customers for each month throughout the entire recorded period, corresponding to each store.

[10]:
```python
# Grouping the QVI data by store number and year-month, then counting the␣
↪unique number of customers for each group
total_customers = qvi_data.groupby(["STORE_NBR",␣
↪"YEAR_MONTH"])["LYLTY_CARD_NBR"].nunique()

# Converting the result from a pandas Series to a pandas DataFrame
total_customers = total_customers.to_frame()

# Displaying the updated pandas DataFrame
total_customers
```

[10]:
```
                      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]
```

Moreover, we can determine the transactions per customer for each recorded month by dividing the count of unique transactions by the count of unique customers for each store.

[11]:
```python
# Grouping the DataFrame by STORE_NBR and YEAR_MONTH, and calculating the␣
↪number of unique transactions per customer
transactions_per_customer = qvi_data.groupby(["STORE_NBR",␣
↪"YEAR_MONTH"])["TXN_ID"].nunique() / qvi_data.groupby(["STORE_NBR",␣
↪"YEAR_MONTH"])["LYLTY_CARD_NBR"].nunique()

# Converting the resulting Series to a DataFrame
transactions_per_customer = transactions_per_customer.to_frame()

# Displaying the updated pandas DataFrame
transactions_per_customer
```

[11]:
```
                             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]
```

[12]:
```python
# Creating a list of all the DataFrames
dataframe_list = [total_sales, total_customers, transactions_per_customer]

# Concatenating all the DataFrames into one
dataframe = pd.concat(dataframe_list, axis=1)

# Renaming the columns of the resulting DataFrame
dataframe.columns = ["TOT_SALES", "TOT_CUST", "TXN_PER_CUST"]

# Displaying the resulting DataFrame
dataframe
```

[12]:
```
                      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]
```

[13]:
```python
# Checking for any null values in the DataFrame
dataframe.isnull().sum()
```

[13]:
```
TOT_SALES       0
TOT_CUST        0
TXN_PER_CUST    0
dtype: int64
```

As the dataset encompasses transaction details for numerous stores, it is possible that certain stores did not document sales throughout the entire duration.

[14]:
```
# Pivot the pandas.DataFrame to obtain the count of transactions recorded for␣
↪each store throughout the entire duration.
recorded_stores = pd.pivot_table(qvi_data, index="STORE_NBR",␣
↪columns="YEAR_MONTH", values="TXN_ID", aggfunc="count")

# Displaying the updated DataFrame
recorded_stores
```

[14]:
```
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]
```

[15]:
```
# Check for any null values in the pandas.DataFrame.
recorded_stores.isnull().sum()
```

[15]:
```
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
```

There are null values for certain months, indicating that some transactions are unrecorded for specific stores. To address this, we should identify and exclude these stores from the dataset, as they cannot serve as control stores.

[16]:
```
# Initialize an empty list to store store numbers with missing data
stores_with_missing_data = []

# Iterate through store numbers in the index of the recorded_stores DataFrame
for store_index in recorded_stores.index:
    # Check if there are any null values for the transactions in each month for
 ↪a store
    if recorded_stores.loc[store_index].isnull().any():
        # If there are null values, add the store number to the list
        stores_with_missing_data.append(store_index)

# Display the list of stores with missing data
stores_with_missing_data
```

[16]:
```
[11, 31, 44, 76, 85, 92, 117, 193, 206, 211, 218, 252]
```

[18]:
```
# Drop rows corresponding to unrecorded stores from the dataframe
dataframe = dataframe.drop(stores_with_missing_data, axis=0)

# Displaying the updated DataFrame
dataframe
```

[18]:
```
                      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 narrow down the dataset to the period before the trial, specifically before February 2022.

[20]:
```python
# Filter the dataset for the pre-trial duration (before February 2019)
pre_trial_data = dataframe[dataframe.index.get_level_values("YEAR_MONTH") <␣
↪"2019-02"].reset_index()

# Displaying the updated DataFrame
pre_trial_data
```

[20]:
```
      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 identify the control stores by excluding those with STORE_NBR 77, 88, and 89.

[26]:
```python
# Filter control stores from the pre-trial dataset, excluding STORE_NBR 77, 86,␣
↪and 88
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"]]

# Group by STORE_NBR and sum the total sales, total customers, and transactions␣
↪per customer for control stores
control_stores = control_stores.groupby(pre_trial_data.STORE_NBR).sum()

# Display the control stores dataset
```

```
control_stores
```

[26]:

```
           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]
```

Similarly, we can filter out the trial stores from the dataset.

[27]:

```
# Extracting data for trial stores (stores 77, 86, and 88) from the pre-trial␣
↪dataset
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()

# Display the trial_stores dataset
trial_stores
```

[27]:

```
           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
```

After filtering both the control stores and the trial stores, we can calculate the Pearson correlation coefficient of the attributes between them. This will help us identify the control stores for each of the trial stores.

For STORE_NBR 77:

[28]:

```
# Calculate the correlation between trial store 77 and control stores
correlation_scores = control_stores.corrwith(trial_stores.loc[77],␣
↪method="pearson", axis=1)

# Get the top five stores with the highest correlation to trial store 77
top_correlated_stores = control_stores.loc[correlation_scores.nlargest(5).index]
```

```
# Calculate the difference between trial store 77 and the top correlated stores
difference = (trial_stores.loc[77] - top_correlated_stores).
 ↪sort_values(by="TOT_SALES", ascending=False)

# Calculate the difference in total sales and sort the DataFrame
difference["DIFFERENCE"] = difference["TOT_SALES"] - difference["TOT_SALES"].
 ↪mean()
difference.sort_values(by="DIFFERENCE", ascending=False)
```

[28]:

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, it is observed that STORE_NBR 46 is the most appropriate choice as the control store.

- STORE_NBR 86:

[29]:

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

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

[29]:

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, it is evident that STORE_NBR 57 would serve as the most appropriate control store.

- STORE_NBR 88:

[30]:
```
# Selecting the top five stores with the highest correlation with the trial␣
↪store (STORE_NBR 88)
difference = control_stores.loc[control_stores.corrwith(trial_stores.loc[88],␣
↪axis=1).nlargest(5).index]

# Calculating the difference between the trial store and the top five stores␣
↪with the highest correlation
difference = (trial_stores.loc[88] - difference).sort_values(by="TOT_SALES",␣
↪ascending=False)
difference["DIFFERENCE"] = difference["TOT_SALES"] - difference["TOT_SALES"].
↪mean()

# Sorting the resulting DataFrame by the DIFFERENCE column
difference.sort_values(by="DIFFERENCE", ascending=False)
```

[30]:

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, STORE_NBR 165 emerges as the most suitable control store. Now, let's compare various control stores to each of the trial stores during the pre-trial duration to identify any significant differences in the statistics.

[31]:
```
# 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()

# 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()

# Concatenating all the pandas.DataFrames into one.
```

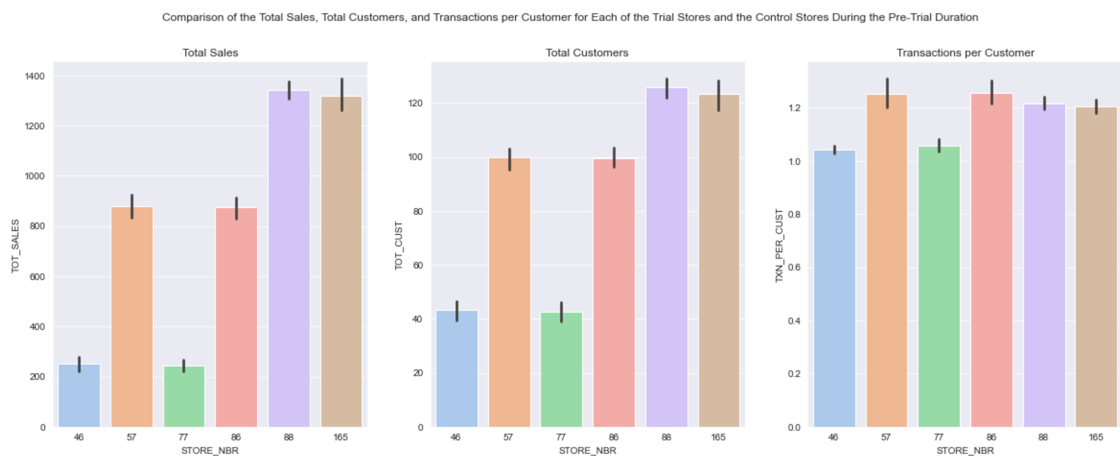
```python
stores = pd.concat([trial_stores_one, trial_stores_two, trial_stores_three,
    control_stores_one, control_stores_two, control_stores_three], axis=0)
stores
```

[31]:

	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

[32]:

```
# 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 of the Trial Stores and the Control␣
↪Stores During the Pre-Trial Duration")
plt.show()
```



Although the performance of the other trial stores matched that of their respective control stores, STORE_NBR 88 demonstrated a slight outperformance across all attributes compared to its control store. Notably, there is a substantial difference in total sales between STORE_NBR 86 and 88, while STORE_NBR 77 exhibits considerably lower sales.

Similarly, we can extend our analysis to compare various control stores with each trial store during the trial duration. This will help us determine if there are significant differences in total sales during the trial period.

[34]:
```python
# Extracting the pandas.DataFrame for the trial duration.
trial_data = dataframe.loc[dataframe.index.get_level_values("YEAR_MONTH") >=␣
↪"2019-02"]
trial_data = trial_data.reset_index()
trial_data
```

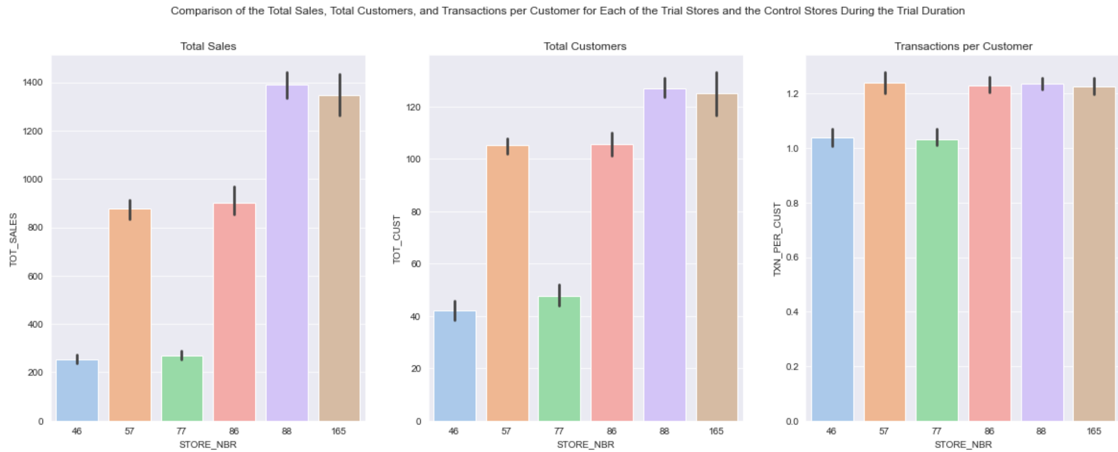
[34]:
```
      STORE_NBR YEAR_MONTH  TOT_SALES  TOT_CUST  TXN_PER_CUST
0             1    2019-02      225.4        52      1.057692
1             1    2019-03      192.9        45      1.088889
2             1    2019-04      192.9        42      1.023810
3             1    2019-05      221.4        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]
```

[35]:
```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()

# 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()

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

[35]:
```
   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

[36]:
```
# 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 of the Trial Stores and the Control
↪Stores During the Trial Duration")
plt.show()
```



Upon further analysis, STORE_NBR 88 continues to exhibit a slight edge over its control store, STORE_NBR 165, making it the most successful trial implementation among all the trial stores. The key factor contributing to this success appears to be an increase in the number of purchasing customers, rather than the number of purchases per customer. Notably, as the total number of customers rises, there is a nearly identical increase in total sales. Additionally, transactions per customer remain reasonably high for all trial stores, irrespective of total sales.

Conclusion: While the performance of other trial stores aligns with their respective control stores, STORE_NBR 88 consistently outperforms its control store, STORE_NBR 165, across all measured attributes. STORE_NBR 86 and 88 demonstrate a significant disparity in total sales, unlike STORE_NBR 77, which may be attributed to variations in the trial implementation.

Considering the substantial variance in total sales among the trial stores, STORE_NBR 88 emerges as the most successful trial implementation. The primary catalyst for the surge in total sales appears to be the influx of purchasing customers, indicating that a higher customer count correlates with increased sales.