Introduction

After completing the first task, the client implemented the suggested market strategies to three trial stores: 77, 86, and 88. The client 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 other stores.

In this analysis, I will be selecting control stores for each trial store and compare their performance. Here are some of the goals for this analysis:

- Select control stores - explore data and define metrics for control store. Look at the drivers and look at them visually to see if they are suitable
- Assess each trial store - Look at each of the trial store and compare them to the control store to see if there are significant difference

In [2]:
```python
#Import
import pandas as pd
import numpy as np

#Visualization
import seaborn as sns
import matplotlib.pyplot as plt

#Date
from datetime import datetime

#Warnings
import warnings
warnings.filterwarnings('ignore')

#Statistics
from scipy.stats import pearsonr

#Regular Expression
import re

#Apriori
from mlxtend.frequent_patterns import apriori
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import association_rules

#Others
from collections import Counter
```

In [3]:
```python
#Import dataset
data = pd.read_csv("QVI_data.csv")
```

In [4]:
```python
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
```

In [5]:
```python
data.describe()
```

Out[5]:

	LYLTY_CARD_NBR	STORE_NBR	TXN_ID	PROD_NBR	PROD_QTY	TOT_SALES	PACK_SIZE
count	2.648340e+05	264834.000000	2.648340e+05	264834.000000	264834.000000	264834.000000	264834.000000
mean	1.355488e+05	135.079423	1.351576e+05	56.583554	1.905813	7.299346	182.425512
std	8.057990e+04	76.784063	7.813292e+04	32.826444	0.343436	2.527241	64.325148
min	1.000000e+03	1.000000	1.000000e+00	1.000000	1.000000	1.500000	70.000000
25%	7.002100e+04	70.000000	6.760050e+04	28.000000	2.000000	5.400000	150.000000
50%	1.303570e+05	130.000000	1.351365e+05	56.000000	2.000000	7.400000	170.000000
75%	2.030940e+05	203.000000	2.026998e+05	85.000000	2.000000	9.200000	175.000000
max	2.373711e+06	272.000000	2.415841e+06	114.000000	5.000000	29.500000	380.000000

In [6]:
```python
data.head()
```

Out[6]:

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	BRAND
0	1000	2018-10-17	1	1	5	Natural Chip Compny SeaSalt175g	2	6.0	175	NATURAL
1	1002	2018-09-16	1	2	58	Red Rock Deli Chikn&Garlic Aioli 150g	1	2.7	150	RRD
2	1003	2019-03-07	1	3	52	Grain Waves Sour Cream&Chives 210G	1	3.6	210	GRNWVES
3	1003	2019-03-08	1	4	106	Natural ChipCo Hony Soy Chckn175g	1	3.0	175	NATURAL
4	1004	2018-11-02	1	5	96	WW Original Stacked Chips 160g	1	1.9	160	WOOLWORTHS

Selecting Control Stores

The client has selected store numbers 77, 86 and 88 as trial stores and want control stores to be established stores that are operational for the entire observation period.

We want to select a store that match trial stores similar to a store before Feb 2019 in terms of:

- Monthly overall sales revenue
- Monthly number of customers
- Monthly number of transactions per customer

Let's start by creating the metrics and filtering the data present to the pre-trial period.

In [7]:
```python
#We will start by creating a Month ID
data["DATE"] = pd.to_datetime(data["DATE"])
data["Month_ID"] = data["DATE"].dt.to_period('M')
data.head()
```

Out[7]:

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	BRAND
0	1000	2018-10-17	1	1	5	Natural Chip Compny SeaSalt175g	2	6.0	175	NATURAL
1	1002	2018-09-16	1	2	58	Red Rock Deli Chikn&Garlic Aioli 150g	1	2.7	150	RRD
2	1003	2019-03-07	1	3	52	Grain Waves Sour Cream&Chives 210G	1	3.6	210	GRNWVES
3	1003	2019-03-08	1	4	106	Natural ChipCo Hony Soy Chckn175g	1	3.0	175	NATURAL
4	1004	2018-11-02	1	5	96	WW Original Stacked Chips 160g	1	1.9	160	WOOLWORTHS

For each store and month we will calculate total sales, number of customers, transactions per customer, chips per customer and the average price per unit.

In [8]:
```python
#Create a new dataframe to store metrics
data_metrics = pd.DataFrame()

#Number of customers
data_metrics["num_customer"] = data.groupby(["STORE_NBR", "Month_ID"]).agg("count")["LYLTY_CARD_NBR"]
data_metrics["num_customer"]
```

Out[8]:
```
STORE_NBR  Month_ID
1          2018-07     52
           2018-08     43
           2018-09     62
           2018-10     45
           2018-11     47
                       ..
272        2019-02     48
           2019-03     53
           2019-04     56
           2019-05     40
           2019-06     37
Name: num_customer, Length: 3169, dtype: int64
```

In [9]:
```python
#Total Sales
data_metrics["tot_sales"] = data.groupby(["STORE_NBR", "Month_ID"]).agg("sum")["TOT_SALES"]
data_metrics["tot_sales"]
```

Out[9]:
```
STORE_NBR  Month_ID
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
Name: tot_sales, Length: 3169, dtype: float64
```

In [10]:
```python
#Average transactions
data_metrics["avg_transaction"] = data.groupby(["STORE_NBR", "Month_ID", "LYLTY_CARD_NBR"]).agg(["coun
t"]).groupby(["STORE_NBR", "Month_ID"]).agg("mean")["DATE"]
data_metrics["avg_transaction"]
```

Out[10]:
```
STORE_NBR  Month_ID
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     1.037037
           2019-05     1.176471
           2019-06     1.088235
Name: avg_transaction, Length: 3169, dtype: float64
```

In [11]:
```python
#Average chips
data_metrics["avg_chips"] = data.groupby(["STORE_NBR", "Month_ID", "LYLTY_CARD_NBR"]).agg(["mean"]).gro
upby(["STORE_NBR", "Month_ID"]).agg("mean")["PROD_QTY"]
data_metrics["avg_chips"]
```

Out[11]:
```
STORE_NBR  Month_ID
1          2018-07     1.183673
           2018-08     1.261905
           2018-09     1.211864
           2018-10     1.295455
           2018-11     1.206522
                         ...
272        2019-02     1.903704
           2019-03     1.910000
           2019-04     1.879630
           2019-05     1.779412
           2019-06     1.911765
Name: avg_chips, Length: 3169, dtype: float64
```

In [12]:
```python
#Average price per unit
data_temp = data[["STORE_NBR", "LYLTY_CARD_NBR", "Month_ID", "PROD_QTY", "TOT_SALES"]]
data_temp["price_per_quantity"] = data_temp["TOT_SALES"]/data_temp["PROD_QTY"]
data_metrics["avg_price_per_quantity"] = data_temp.groupby(["STORE_NBR", "Month_ID"]).agg("mean")["pric
e_per_quantity"]
data_metrics["avg_price_per_quantity"]
```

Out[12]:
```
STORE_NBR  Month_ID
1          2018-07     3.384615
           2018-08     3.329070
           2018-09     3.685484
           2018-10     3.288889
           2018-11     3.412766
                         ...
272        2019-02     4.358333
           2019-03     4.350943
           2019-04     4.248214
           2019-05     4.437500
           2019-06     4.424324
Name: avg_price_per_quantity, Length: 3169, dtype: float64
```

In [13]:
```python
data_metrics = data_metrics.reset_index(level=['STORE_NBR', 'Month_ID'])
```

In [14]:
```python
data_counts = data_metrics.groupby("STORE_NBR").agg("count")["Month_ID"]
store_list = data_counts[data_counts == 12].index.to_list()
data_metrics_fs = data_metrics[data_metrics["STORE_NBR"].isin(store_list)]
data_metrics_fs
```

Out[14]:

	STORE_NBR	Month_ID	num_customer	tot_sales	avg_transaction	avg_chips	avg_price_per_quantity
0	1	2018-07	52	206.9	1.061224	1.183673	3.384615
1	1	2018-08	43	176.1	1.023810	1.261905	3.329070
2	1	2018-09	62	278.8	1.050847	1.211864	3.685484
3	1	2018-10	45	188.1	1.022727	1.295455	3.288889
4	1	2018-11	47	192.6	1.021739	1.206522	3.412766
...	...	...	...	...	...	...	...
3164	272	2019-02	48	395.5	1.066667	1.903704	4.358333
3165	272	2019-03	53	442.3	1.060000	1.910000	4.350943
3166	272	2019-04	56	445.1	1.037037	1.879630	4.248214
3167	272	2019-05	40	314.6	1.176471	1.779412	4.437500
3168	272	2019-06	37	312.1	1.088235	1.911765	4.424324

3120 rows × 7 columns

In [15]:
```python
data_metrics_fs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3120 entries, 0 to 3168
Data columns (total 7 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   STORE_NBR               3120 non-null   int64
 1   Month_ID                3120 non-null   period[M]
 2   num_customer            3120 non-null   int64
 3   tot_sales               3120 non-null   float64
 4   avg_transaction         3120 non-null   float64
 5   avg_chips               3120 non-null   float64
 6   avg_price_per_quantity  3120 non-null   float64
dtypes: float64(4), int64(2), period[M](1)
memory usage: 195.0 KB
```

In [16]:
```python
#Now we filter only values before Febuary 2019 (Pre-trial period)
data_metrics_pre = data_metrics_fs[data_metrics_fs["Month_ID"] < "2019-02"]
data_metrics_pre["Month_ID"].unique()
```

Out[16]:
```
<PeriodArray>
['2018-07', '2018-08', '2018-09', '2018-10', '2018-11', '2018-12', '2019-01']
Length: 7, dtype: period[M]
```

Next, we will create a function to calculate the correlation between the trial store and the control store.

In [17]:
```python
def CalculateCorrelation(input_table, metric_col, store_comparison):
    store_numbers = input_table["STORE_NBR"].unique()
    coorList = []
    for i in store_numbers:
        store_numbers = input_table["STORE_NBR"].unique()
        store_1 = store_comparison
        store_2 = i
        store_trial = input_table[input_table["STORE_NBR"] == store_1][metric_col]
        store_control = input_table[input_table["STORE_NBR"] == store_2][metric_col]
        coor_measure = pearsonr(store_trial, store_control)[0]
        coorList.append([store_1, store_2, coor_measure])
    correlationTable = pd.DataFrame(coorList, columns=["STORE1", "STORE2", "COORMEASURE"])
    return correlationTable
```

Aside from correlation, we can also calculate a standardized metric based on the absolute difference between the trial store's performance and each control store's performance.

In [18]:
```python
def CalculateMagnitudeDistance (input_table, metric_col, store_comparison):
    # Find abs value between trial and control
    # standardize
    distdf = pd.DataFrame()
    store_numbers = data_metrics_pre["STORE_NBR"].unique()
    data_list = []

    for i in store_numbers:
        store_1 = store_comparison
        store_2 = i
        grouped_metrics = input_table.groupby(["Month_ID", "STORE_NBR"]).agg("sum")[metric_col]
        grouped_metrics = grouped_metrics.reset_index(level="STORE_NBR")
        measure = np.abs(grouped_metrics[grouped_metrics["STORE_NBR"] == store_1][metric_col] - grouped
_metrics[grouped_metrics["STORE_NBR"] == store_2][metric_col])
        measure = measure.reset_index()
        measure["STORE1"] = store_1
        measure["STORE2"] = store_2
        distdf = pd.concat([measure, distdf], axis=0)
    #Reset distdf index
    distdf = distdf.reset_index(drop=True)

    #Standardize the values
    grouped_table = distdf.groupby(["STORE1", "Month_ID"]).agg(["max", "min"])[metric_col]
    grouped_table = grouped_table.reset_index()

    #Change Month-ID to string so we can use df.merge()
    distdf["YEARMONTH"] = distdf["Month_ID"].astype(str).str.replace('-','')
    distdf = distdf.drop("Month_ID", axis=1)
    grouped_table["YEARMONTH"] = grouped_table["Month_ID"].astype(str).str.replace('-','')
    grouped_table = grouped_table.drop("Month_ID", axis=1)

    distdf = distdf.merge(grouped_table, on=["STORE1", "YEARMONTH"])
    distdf[metric_col] = 1-((distdf[metric_col] - distdf["min"])/(distdf["max"] - distdf["min"]))
    final_dist_df = distdf.groupby(["STORE1", "STORE2"]).agg("mean")[metric_col]
    final_dist_df = final_dist_df.reset_index()
    return final_dist_df
```

Now that the functions are set, we will use those functions to show how related each store is to the trial store. This will help us choose our control store.

In [19]:
```python
trial_store = 77
corr_nSales = CalculateCorrelation(data_metrics_pre, "tot_sales", trial_store)
corr_nSales
```

Out[19]:

	STORE1	STORE2	COORMEASURE
0	77	1	0.075218
1	77	2	-0.263079
2	77	3	0.806644
3	77	4	-0.263300
4	77	5	-0.110652
...	...	...	...
255	77	268	0.344757
256	77	269	-0.315730
257	77	270	0.315430
258	77	271	0.355487
259	77	272	0.117622

260 rows × 3 columns

In [20]:
```python
magnitude_nSales = CalculateMagnitudeDistance(data_metrics_pre, "tot_sales", trial_store)
magnitude_nSales
```

Out[20]:

	STORE1	STORE2	tot_sales
0	77	1	0.953285
1	77	2	0.937579
2	77	3	0.354315
3	77	4	0.177135
4	77	5	0.553043
...	...	...	...
255	77	268	0.960785
256	77	269	0.452134
257	77	270	0.446082
258	77	271	0.552318
259	77	272	0.885088

260 rows × 3 columns

In [21]:
```python
corr_nCustomer = CalculateCorrelation(data_metrics_pre, "num_customer", trial_store)
corr_nCustomer
```

Out[21]:

	STORE1	STORE2	COORMEASURE
0	77	1	0.355839
1	77	2	-0.379313
2	77	3	0.861748
3	77	4	-0.181233
4	77	5	0.434760
...	...	...	...
255	77	268	0.420250
256	77	269	-0.404251
257	77	270	0.294484
258	77	271	0.238140
259	77	272	0.103679

260 rows × 3 columns

In [22]:
```python
magnitude_nCustomer = CalculateMagnitudeDistance(data_metrics_pre, "num_customer", trial_store)
magnitude_nCustomer
```

Out[22]:

	STORE1	STORE2	num_customer
0	77	1	0.954562
1	77	2	0.943671
2	77	3	0.389224
3	77	4	0.208682
4	77	5	0.455735
...	...	...	...
255	77	268	0.953317
256	77	269	0.307023
257	77	270	0.283301
258	77	271	0.459194
259	77	272	0.958953

260 rows × 3 columns

Now, we can combine these two tables and use a simple average to calculate the score for each store.

In [23]:
```python
score_nSales = corr_nSales.merge(magnitude_nSales, on=["STORE1", "STORE2"])
score_nSales = score_nSales.rename({"tot_sales": "MAGNITUDESALES"}, axis=1)
score_nSales["scoreNSales"] = (0.5*score_nSales["COORMEASURE"] + 0.5*score_nSales["MAGNITUDESALES"])
score_nSales
```

Out[23]:

	STORE1	STORE2	COORMEASURE	MAGNITUDESALES	scoreNSales
0	77	1	0.075218	0.953285	0.514251
1	77	2	-0.263079	0.937579	0.337250
2	77	3	0.806644	0.354315	0.580479
3	77	4	-0.263300	0.177135	-0.043082
4	77	5	-0.110652	0.553043	0.221196
...	...	...	...	...	...
255	77	268	0.344757	0.960785	0.652771
256	77	269	-0.315730	0.452134	0.068202
257	77	270	0.315430	0.446082	0.380756
258	77	271	0.355487	0.552318	0.453902
259	77	272	0.117622	0.885088	0.501355

260 rows × 5 columns

In [24]:
```python
score_nCust = corr_nCustomer.merge(magnitude_nCustomer, on=["STORE1", "STORE2"])
score_nCust = score_nCust.rename({"num_customer": "MAGNITUDECUST"}, axis=1)
score_nCust["scoreNCust"] = (0.5*score_nCust["COORMEASURE"] + 0.5*score_nCust["MAGNITUDECUST"])
score_nCust
```

Out[24]:

	STORE1	STORE2	COORMEASURE	MAGNITUDECUST	scoreNCust
0	77	1	0.355839	0.954562	0.655200
1	77	2	-0.379313	0.943671	0.282179
2	77	3	0.861748	0.389224	0.625486
3	77	4	-0.181233	0.208682	0.013725
4	77	5	0.434760	0.455735	0.445248
...	...	...	...	...	...
255	77	268	0.420250	0.953317	0.686784
256	77	269	-0.404251	0.307023	-0.048614
257	77	270	0.294484	0.283301	0.288892
258	77	271	0.238140	0.459194	0.348667
259	77	272	0.103679	0.958953	0.531316

260 rows × 5 columns

In [25]:
```python
score_control = score_nCust.merge(score_nSales, on=["STORE1", "STORE2"])
score_control = score_control.drop(["COORMEASURE_x", "MAGNITUDECUST", "COORMEASURE_y", "MAGNITUDESALES"
], axis=1)
score_control["finalControlScore"] = np.abs(score_control["scoreNSales"] * 0.5 + score_control["scoreNC
ust"] * 0.5)
score_control
```

Out[25]:

	STORE1	STORE2	scoreNCust	scoreNSales	finalControlScore
0	77	1	0.655200	0.514251	0.584726
1	77	2	0.282179	0.337250	0.309715
2	77	3	0.625486	0.580479	0.602983
3	77	4	0.013725	-0.043082	0.014679
4	77	5	0.445248	0.221196	0.333222
...	...	...	...	...	...
255	77	268	0.686784	0.652771	0.669778
256	77	269	-0.048614	0.068202	0.009794
257	77	270	0.288892	0.380756	0.334824
258	77	271	0.348667	0.453902	0.401285
259	77	272	0.531316	0.501355	0.516336

260 rows × 5 columns

To choose our control store, we will find a store with highest final score.

In [26]:
```python
score_control.sort_values(by="finalControlScore", ascending=False)
```

Out[26]:

	STORE1	STORE2	scoreNCust	scoreNSales	finalControlScore
72	77	77	1.000000	1.000000	1.000000
221	77	233	0.974736	0.944520	0.959628
38	77	41	0.928552	0.874186	0.901369
15	77	17	0.903821	0.861678	0.882750
108	77	115	0.886045	0.810995	0.848520
...	...	...	...	...	...
147	77	155	-0.054960	0.087850	0.016445
3	77	4	0.013725	-0.043082	0.014679
107	77	114	0.015887	0.009057	0.012472
256	77	269	-0.048614	0.068202	0.009794
80	77	86	-0.111328	0.122386	0.005529

260 rows × 5 columns

The highest score is given by store 233 with the score of 0.96. To make sure we have selected the appropriate control store, we will check the performance of this score visually.

In [27]:
```python
def updateStores(col):
    if int(col) == 233:
        return "Control"
    elif int(col) == 77:
        return "Trial"
    else:
        return "Others"
```

In [28]:
```python
trial_store = 77
control_store = 233

measure_over_time = data_metrics_pre.copy()
measure_over_time["STORE_TYPE"] = measure_over_time["STORE_NBR"].apply(updateStores)
measure_over_time["STORE_TYPE"].unique()
measure_over_time
```

Out[28]:

	STORE_NBR	Month_ID	num_customer	tot_sales	avg_transaction	avg_chips	avg_price_per_quantity	STORE_TYPE
0	1	2018-07	52	206.9	1.061224	1.183673	3.384615	Others
1	1	2018-08	43	176.1	1.023810	1.261905	3.329070	Others
2	1	2018-09	62	278.8	1.050847	1.211864	3.685484	Others
3	1	2018-10	45	188.1	1.022727	1.295455	3.288889	Others
4	1	2018-11	47	192.6	1.021739	1.206522	3.412766	Others
...	...	...	...	...	...	...	...	...
3159	272	2018-09	36	304.7	1.125000	1.989583	4.283333	Others
3160	272	2018-10	51	430.6	1.159091	1.943182	4.345098	Others
3161	272	2018-11	45	376.2	1.097561	1.926829	4.308889	Others
3162	272	2018-12	47	403.9	1.000000	1.893617	4.512766	Others
3163	272	2019-01	50	423.0	1.086957	1.913043	4.410000	Others

1820 rows × 8 columns

In [29]:
```python
pastSales = measure_over_time.groupby(["STORE_TYPE", "Month_ID"]).agg("mean")["tot_sales"].reset_index
()
pastSales["Month_ID"] = pastSales["Month_ID"].astype(str).str.replace("-", "").astype(float)
pastSales
```

Out[29]:

	STORE_TYPE	Month_ID	tot_sales
0	Control	201807.0	290.700000
1	Control	201808.0	285.900000
2	Control	201809.0	228.600000
3	Control	201810.0	185.700000
4	Control	201811.0	211.600000
5	Control	201812.0	279.800000
6	Control	201901.0	177.500000
7	Others	201807.0	638.004651
8	Others	201808.0	610.223450
9	Others	201809.0	620.198450
10	Others	201810.0	635.314729
11	Others	201811.0	618.864341
12	Others	201812.0	648.453876
13	Others	201901.0	628.684496
14	Trial	201807.0	296.800000
15	Trial	201808.0	255.500000
16	Trial	201809.0	225.200000
17	Trial	201810.0	204.500000
18	Trial	201811.0	245.300000
19	Trial	201812.0	267.300000
20	Trial	201901.0	204.400000

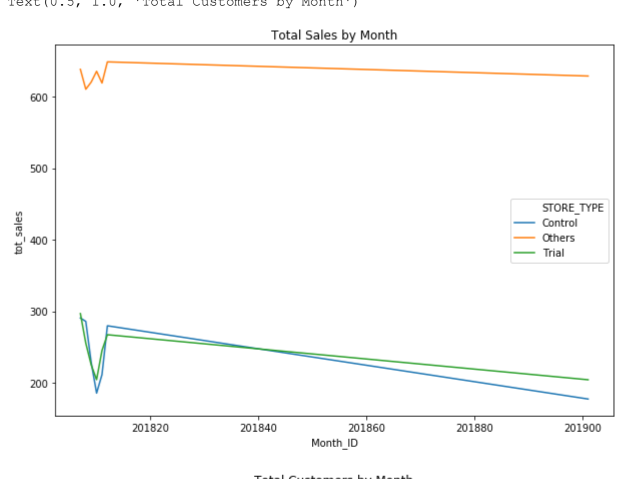
In [30]:
```python
pastCust = measure_over_time.groupby(["STORE_TYPE", "Month_ID"]).agg("mean")["num_customer"].reset_inde
x()
pastCust["Month_ID"] = pastCust["Month_ID"].astype(str).str.replace("-", "").astype(float)
pastCust
```

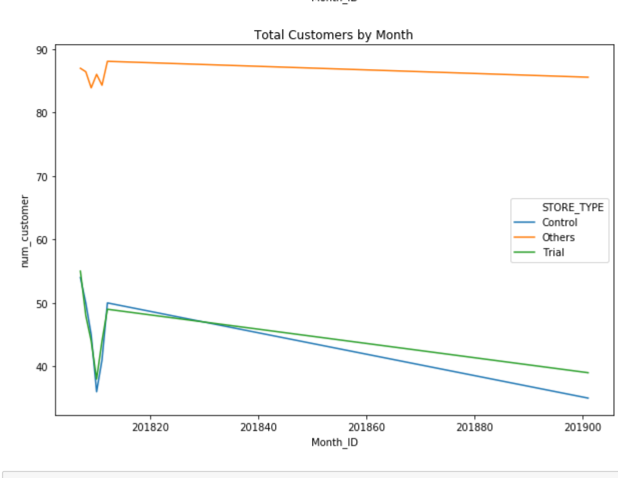
Out[30]:

	STORE_TYPE	Month_ID	num_customer
0	Control	201807.0	54.000000
1	Control	201808.0	50.000000
2	Control	201809.0	45.000000
3	Control	201810.0	36.000000
4	Control	201811.0	41.000000
5	Control	201812.0	50.000000
6	Control	201901.0	35.000000
7	Others	201807.0	86.965116
8	Others	201808.0	86.418605
9	Others	201809.0	83.879845
10	Others	201810.0	86.011628
11	Others	201811.0	84.290698
12	Others	201812.0	88.062016
13	Others	201901.0	85.558140
14	Trial	201807.0	55.000000
15	Trial	201808.0	48.000000
16	Trial	201809.0	44.000000
17	Trial	201810.0	38.000000
18	Trial	201811.0	44.000000
19	Trial	201812.0	49.000000
20	Trial	201901.0	39.000000

In [31]:
```python
fig = plt.figure(figsize=(10,15))
ax1 = fig.add_subplot(2,1,1)
ax2 = fig.add_subplot(2,1,2)
sns.lineplot(x=pastSales["Month_ID"], y=pastSales["tot_sales"], hue=pastSales["STORE_TYPE"], ax=ax1).se
t_title("Total Sales by Month")
sns.lineplot(x=pastCust["Month_ID"], y=pastCust["num_customer"], hue=pastCust["STORE_TYPE"], ax=ax2).se
t_title("Total Customers by Month")
```

Out[31]:
```
Text(0.5, 1.0, 'Total Customers by Month')
```





In [32]:
```python
data_metrics_pre["Month_ID"] = data_metrics_pre["Month_ID"].astype(str).str.replace("-", "").astype(flo
at)
trial_metrics = data_metrics_pre[(data_metrics_pre["STORE_NBR"] == trial_store) & (data_metrics_pre["Mo
nth_ID"] < 201902)]["tot_sales"]
control_metrics = data_metrics_pre[(data_metrics_pre["STORE_NBR"] == control_store) & (data_metrics_pre
["Month_ID"] < 201902)]["tot_sales"]

scalingFactorForControlSales = trial_metrics.sum()/control_metrics.sum()
scalingFactorForControlSales
```

Out[32]:
```
1.023617303289553
```

In [53]:
```python
data_metrics_sales = data_metrics_fs.copy()
scaled_control_sales = data_metrics_sales[data_metrics_sales["STORE_NBR"] == control_store]
scaled_control_sales["controlSales"] = data_metrics_sales["tot_sales"]*scalingFactorForControlSales
scaled_control_sales = scaled_control_sales.drop(["num_customer", "tot_sales", "avg_transaction","avg_c
hips","avg_price_per_quantity"], axis=1).reindex()
scaled_control_sales
```

Out[53]:

	STORE_NBR	Month_ID	controlSales
2699	233	2018-07	297.565550
2700	233	2018-08	292.652187
2701	233	2018-09	233.998916
2702	233	2018-10	190.085733
2703	233	2018-11	216.597421
2704	233	2018-12	286.408121
2705	233	2019-01	181.692071
2706	233	2019-02	249.762622
2707	233	2019-03	203.802205
2708	233	2019-04	162.345704
2709	233	2019-05	352.533799
2710	233	2019-06	226.219424

Now that we have comparable sales figures, we can find the percentage difference between the scaled control store and trial store's during the trial period.

In [156]:

```
trial_df_totsales = data_metrics_fs[data_metrics_fs["STORE_NBR"] == trial_store].drop(["avg_transactio
n", "avg_chips", "avg_price_per_quantity", "num_customer"], axis=1)
trial_df_totsales
```

Out[156]:

	STORE_NBR	Month_ID	tot_sales
880	77	2018-07	296.8
881	77	2018-08	255.5
882	77	2018-09	225.2
883	77	2018-10	204.5
884	77	2018-11	245.3
885	77	2018-12	267.3
886	77	2019-01	204.4
887	77	2019-02	235.0
888	77	2019-03	278.5
889	77	2019-04	263.5
890	77	2019-05	299.3
891	77	2019-06	264.7

In [158]:

```
percent_dif = trial_df_totsales.merge(scaled_control_sales, on=("Month_ID")).rename({"STORE_NBR_x": "T
RIAL", "STORE_NBR_y": "CONTROL"}, axis=1)
percent_dif = percent_dif[["TRIAL", "CONTROL", "Month_ID", "tot_sales", "controlSales"]]
percent_dif["percentage_difference"] = np.abs((percent_dif["tot_sales"] - percent_dif["controlSales"])
/((percent_dif["tot_sales"] + percent_dif["controlSales"])/2))
percent_dif
```

Out[158]:

	TRIAL	CONTROL	Month_ID	tot_sales	controlSales	percentage_difference
0	77	233	2018-07	296.8	297.565550	0.002576
1	77	233	2018-08	255.5	292.652187	0.135554
2	77	233	2018-09	225.2	233.998916	0.038323
3	77	233	2018-10	204.5	190.085733	0.073060
4	77	233	2018-11	245.3	216.597421	0.124281
5	77	233	2018-12	267.3	286.408121	0.069019
6	77	233	2019-01	204.4	181.692071	0.117630
7	77	233	2019-02	235.0	249.762622	0.060907
8	77	233	2019-03	278.5	203.802205	0.309755
9	77	233	2019-04	263.5	162.345704	0.475075
10	77	233	2019-05	299.3	352.533799	0.163335
11	77	233	2019-06	264.7	226.219424	0.156769

We need to see if the difference is significant.

- H0: trial = pre-trial
- H1: trial ≠ pre-trial

In [67]:

```
#Take standard deviation of percentage difference
stdDev = percent_dif["percentage_difference"].std()
stdDev
```

Out[67]: 0.13056002105171627

In [69]:

```
#There are 8 months in the pre-trial period so degrees of freedom = 8 - 1 = 7
degreesOfFreedom = 7

#We will test the null hypothesis being 0 difference between trial and control stores
percent_dif["tvalue"] = np.abs(percent_dif["percentage_difference"] - percent_dif["percentage_differenc
e"].mean())/stdDev
percent_dif
```

Out[69]:

	TRIAL	CONTROL	Month_ID	tot_sales	controlSales	percentage_difference	tvalue
0	77	233	2018-07	296.8	297.565550	0.002576	1.082115
1	77	233	2018-08	255.5	292.652187	0.135554	0.063593
2	77	233	2018-09	225.2	233.998916	0.038323	0.808319
3	77	233	2018-10	204.5	190.085733	0.073060	0.542255
4	77	233	2018-11	245.3	216.597421	0.124281	0.149938
5	77	233	2018-12	267.3	286.408121	0.069019	0.573210
6	77	233	2019-01	204.4	181.692071	0.117630	0.200884
7	77	233	2019-02	235.0	249.762622	0.060907	0.635343
8	77	233	2019-03	278.5	203.802205	0.309755	1.270665
9	77	233	2019-04	263.5	162.345704	0.475075	2.536901
10	77	233	2019-05	299.3	352.533799	0.163335	0.149192
11	77	233	2019-06	264.7	226.219424	0.156769	0.098900

In [71]:

```
#Let's filter for the trial period
percent_trial = percent_dif[percent_dif["Month_ID"] > "2019-01"]
percent_trial
```

Out[71]:

	TRIAL	CONTROL	Month_ID	tot_sales	controlSales	percentage_difference	tvalue
7	77	233	2019-02	235.0	249.762622	0.060907	0.635343
8	77	233	2019-03	278.5	203.802205	0.309755	1.270665
9	77	233	2019-04	263.5	162.345704	0.475075	2.536901
10	77	233	2019-05	299.3	352.533799	0.163335	0.149192
11	77	233	2019-06	264.7	226.219424	0.156769	0.098900

We can observe that the tvalue is much larger than 95th percentile value of the t-distribution for March and April. This means that the increase in sales in the trial store in March and April is significantly greater than in the control store. Let's get a better look by plotting the sales of the control store, sales of the trial store, and the 95th percentile value of sales of the control store.

In [150]:

```
measure_over_time_sales = data_metrics_fs[["STORE_NBR", "Month_ID", "tot_sales"]]
measure_over_time_sales["Month_ID"] = measure_over_time_sales["Month_ID"].astype(str).str.replace("-",
 "").astype(int)
measure_over_time_sales["STORE_NBR"] = measure_over_time_sales["STORE_NBR"].apply(updateStores)
measure_over_time_sales = measure_over_time_sales.rename({"STORE_NBR": "STORE_TYPE"}, axis=1)
measure_over_time_sales = measure_over_time_sales[measure_over_time_sales["STORE_TYPE"].isin(["Contro
l", "Trial"])]

#Control Store 95th Percentile
pastSales_control95 = measure_over_time_sales[measure_over_time_sales["STORE_TYPE"] == "Control"]
pastSales_control95["tot_sales"] = pastSales_control95["tot_sales"] * (1 + stdDev * 2)
pastSales_control95["STORE_TYPE"] = "Control 95th % confidence interval"
pastSales_control95

#Control Store 95th Percentile
pastSales_control5 = measure_over_time_sales[measure_over_time_sales["STORE_TYPE"] == "Control"]
pastSales_control5["tot_sales"] = pastSales_control5["tot_sales"] * (1 - stdDev * 2)
pastSales_control5["STORE_TYPE"] = "Control 5th % confidence interval"
pastSales_control5

trialAssesment = pd.concat([measure_over_time_sales, pastSales_control95, pastSales_control5])
trialAssesment
trialAssesment_month = trialAssesment[(trialAssesment["Month_ID"] > 201901) & (trialAssesment["Month_I
D"] < 201905)]
month_label = trialAssesment_month["Month_ID"].astype(str).unique()

#Plot into a graph
fig = plt.figure(figsize=(15,10))
ax1 = fig.add_subplot(1,1,1)
sns.lineplot(x="Month_ID", y="tot_sales", hue="STORE_TYPE", data=trialAssesment_month, ax=ax1).set_tit
le("Total Sales by Month")
```

Out[150]: Text(0.5, 1.0, 'Total Sales by Month')

The results show that the trial in store 77 is significantly different to its control store in the trial period since the trial store performance lies outside of the 5% and 95% confidence interval of the control store in two out of three trial months.

Let's asses this for the number of customers as well.

In [151]:

```
data_metrics_pre["Month_ID"] = data_metrics_pre["Month_ID"].astype(str).str.replace("-", "").astype(fl
oat)
trial_metrics = data_metrics_pre[(data_metrics_pre["STORE_NBR"] == trial_store) & (data_metrics_pre["M
onth_ID"] < 201902)]["num_customer"]
control_metrics = data_metrics_pre[(data_metrics_pre["STORE_NBR"] == control_store) & (data_metrics_pr
e["Month_ID"] < 201902)]["num_customer"]

scalingFactorForControlCust = trial_metrics.sum()/control_metrics.sum()
scalingFactorForControlCust
```

Out[151]: 1.0192926045016077

In [153]:

```
data_metrics_cust = data_metrics_fs.copy()
scaled_control_cust = data_metrics_cust[data_metrics_cust["STORE_NBR"] == control_store]
scaled_control_cust["controlCust"] = data_metrics_cust["tot_sales"]*scalingFactorForControlCust
scaled_control_cust = scaled_control_cust.drop(["num_customer", "tot_sales", "avg_transaction","avg_ch
ips","avg_price_per_quantity"], axis=1).reindex()
scaled_control_cust
```

Out[153]:

	STORE_NBR	Month_ID	controlCust
2699	233	2018-07	296.308360
2700	233	2018-08	291.415756
2701	233	2018-09	233.010289
2702	233	2018-10	189.282637
2703	233	2018-11	215.682315
2704	233	2018-12	285.198071
2705	233	2019-01	180.924437
2706	233	2019-02	248.707395
2707	233	2019-03	202.941158
2708	233	2019-04	161.659807
2709	233	2019-05	351.044373
2710	233	2019-06	225.263666

In [159]:

```
trial_df_cust = data_metrics_fs[data_metrics_fs["STORE_NBR"] == trial_store].drop(["avg_transaction",
"avg_chips", "avg_price_per_quantity", "tot_sales"], axis=1)
trial_df_cust
```

Out[159]:

	STORE_NBR	Month_ID	num_customer
880	77	2018-07	55
881	77	2018-08	48
882	77	2018-09	44
883	77	2018-10	38
884	77	2018-11	44
885	77	2018-12	49
886	77	2019-01	39
887	77	2019-02	45
888	77	2019-03	55
889	77	2019-04	48
890	77	2019-05	56
891	77	2019-06	42

In [163]:

```
percent_dif_cust = trial_df_cust.merge(scaled_control_cust, on=("Month_ID")).rename({"STORE_NBR_x": "T
RIAL", "STORE_NBR_y": "CONTROL"}, axis=1)
percent_dif_cust = percent_dif_cust[["TRIAL", "CONTROL", "Month_ID", "num_customer", "controlCust"]]
percent_dif_cust["percentage_difference"] = np.abs((percent_dif_cust["num_customer"] - percent_dif_cus
t["controlCust"])/((percent_dif_cust["num_customer"] + percent_dif_cust["controlCust"])/2))
percent_dif_cust
```

Out[163]:

	TRIAL	CONTROL	Month_ID	num_customer	controlCust	percentage_difference
0	77	233	2018-07	55	296.308360	1.373770
1	77	233	2018-08	48	291.415756	1.434322
2	77	233	2018-09	44	233.010289	1.364645
3	77	233	2018-10	38	189.282637	1.331229
4	77	233	2018-11	44	215.682315	1.322249
5	77	233	2018-12	49	285.198071	1.413521
6	77	233	2019-01	39	180.924437	1.290665
7	77	233	2019-02	45	248.707395	1.387145
8	77	233	2019-03	55	202.941158	1.147092
9	77	233	2019-04	48	161.659807	1.084231
10	77	233	2019-05	56	351.044373	1.449691
11	77	233	2019-06	42	225.263666	1.371407

In [164]:

```
#Take standard deviation of percentage difference
stdDev_cust = percent_dif_cust["percentage_difference"].std()

#There are 8 months in the pre-trial period so degrees of freedom = 8 - 1 = 7
degreesOfFreedom = 7

#We will test the null hypothesis being 0 difference between trial and control stores
percent_dif_cust["tvalue"] = np.abs(percent_dif_cust["percentage_difference"] - percent_dif_cust["perc
entage_difference"].mean())/stdDev
percent_dif_cust
```

Out[164]:

	TRIAL	CONTROL	Month_ID	num_customer	controlCust	percentage_difference	tvalue
0	77	233	2018-07	55	296.308360	1.373770	0.328882
1	77	233	2018-08	48	291.415756	1.434322	0.792673
2	77	233	2018-09	44	233.010289	1.364645	0.258991
3	77	233	2018-10	38	189.282637	1.331229	0.003052
4	77	233	2018-11	44	215.682315	1.322249	0.065731
5	77	233	2018-12	49	285.198071	1.413521	0.633355
6	77	233	2019-01	39	180.924437	1.290665	0.307638
7	77	233	2019-02	45	248.707395	1.387145	0.431330
8	77	233	2019-03	55	202.941158	1.147092	1.407310
9	77	233	2019-04	48	161.659807	1.084231	1.888786
10	77	233	2019-05	56	351.044373	1.449691	0.910392
11	77	233	2019-06	42	225.263666	1.371407	0.310789

In [165]:

```
#Let's filter for the trial period
percent_trial = percent_dif_cust[percent_dif_cust["Month_ID"] > "2019-01"]
percent_trial
```

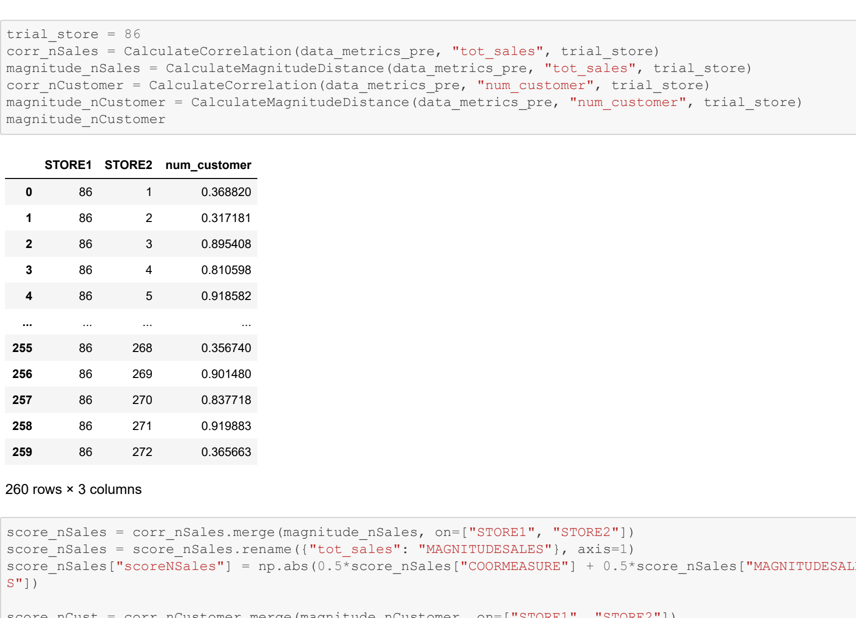
Out[165]:

	TRIAL	CONTROL	Month_ID	num_customer	controlCust	percentage_difference	tvalue
7	77	233	2019-02	45	248.707395	1.387145	0.431330
8	77	233	2019-03	55	202.941158	1.147092	1.407310
9	77	233	2019-04	48	161.659807	1.084231	1.888786
10	77	233	2019-05	56	351.044373	1.449691	0.910392
11	77	233	2019-06	42	225.263666	1.371407	0.310789

In [167]:

```
measure_over_time_cust = data_metrics_fs[["STORE_NBR", "Month_ID", "num_customer"]]
measure_over_time_cust["Month_ID"] = measure_over_time_cust["Month_ID"].astype(str).str.replace("-",
"").astype(int)
measure_over_time_cust["STORE_NBR"] = measure_over_time_cust["STORE_NBR"].apply(updateStores)
measure_over_time_cust = measure_over_time_cust.rename({"STORE_NBR": "STORE_TYPE"}, axis=1)
measure_over_time_cust = measure_over_time_cust[measure_over_time_cust["STORE_TYPE"].isin(["Control",
"Trial"])]

#Control Store 95th Percentile
pastCust_control95 = measure_over_time_cust[measure_over_time_cust["STORE_TYPE"] == "Control"]
pastCust_control95["num_customer"] = pastCust_control95["num_customer"] * (1 + stdDev_cust * 2)
pastCust_control95["STORE_TYPE"] = "Control 95th % confidence interval"
pastCust_control95

#Control Store 95th Percentile
pastCust_control5 = measure_over_time_cust[measure_over_time_cust["STORE_TYPE"] == "Control"]
pastCust_control5["num_customer"] = pastCust_control5["num_customer"] * (1 - stdDev * 2)
pastCust_control5["STORE_TYPE"] = "Control 5th % confidence interval"
pastCust_control5

trialAssesment = pd.concat([measure_over_time_cust, pastCust_control95, pastCust_control5])
trialAssesment
trialAssesment_month = trialAssesment[(trialAssesment["Month_ID"] > 201901) & (trialAssesment["Month_I
D"] < 201905)]
month_label = trialAssesment_month["Month_ID"].astype(str).unique()

#Plot into a graph
fig = plt.figure(figsize=(15,10))
ax1 = fig.add_subplot(1,1,1)
sns.lineplot(x="Month_ID", y="num_customer", hue="STORE_TYPE", data=trialAssesment_month, ax=ax1).set_
title("Total Customer by Month")
```

Out[167]: Text(0.5, 1.0, 'Total Customer by Month')



Let's find the control stores for the other two trial stores.

Trial Store 86

In [196]:

```
trial_store = 86
corr_nSales = CalculateCorrelation(data_metrics_pre, "tot_sales", trial_store)
magnitude_nSales = CalculateMagnitudeDistance(data_metrics_pre, "tot_sales", trial_store)
corr_nCustomer = CalculateCorrelation(data_metrics_pre, "num_customer", trial_store)
magnitude_nCustomer = CalculateMagnitudeDistance(data_metrics_pre, "num_customer", trial_store)
magnitude_nCustomer
```

Out[196]:

	STORE1	STORE2	num_customer
0	86	1	0.368820
1	86	2	0.317181
2	86	3	0.895408
3	86	4	0.810598
4	86	5	0.918582
...	...	...	...
255	86	268	0.356740
256	86	269	0.901480
257	86	270	0.837718
258	86	271	0.919883
259	86	272	0.365663

260 rows × 3 columns

In [197]:

```
score_nSales = corr_nSales.merge(magnitude_nSales, on=["STORE1", "STORE2"])
score_nSales = score_nSales.rename({"tot_sales": "MAGNITUDESALES"}, axis=1)
score_nSales["scoreNSales"] = np.abs(0.5*score_nSales["COORMEASURE"] + 0.5*score_nSales["MAGNITUDESALE
S"])

score_nCust = corr_nCustomer.merge(magnitude_nCustomer, on=["STORE1", "STORE2"])
score_nCust = score_nCust.rename({"num_customer": "MAGNITUDECUST"}, axis=1)
score_nCust["scoreNCust"] = np.abs(0.5*score_nCust["COORMEASURE"] + 0.5*score_nCust["MAGNITUDECUST"])

score_control = score_nCust.merge(score_nSales, on=["STORE1", "STORE2"])
score_control = score_control.drop(["COORMEASURE_x", "MAGNITUDECUST", "COORMEASURE_y", "MAGNITUDESALE
S"], axis=1)
score_control["finalControlScore"] = np.abs(score_control["scoreNSales"] * 0.5 + score_control["scoreN
Cust"] * 0.5)
score_control.sort_values(by="finalControlScore", ascending=False)
```

Out[197]:

	STORE1	STORE2	scoreNCust	scoreNSales	finalControlScore
80	86	86	1.000000	1.000000	1.000000
130	86	138	0.899832	0.841792	0.870812
147	86	155	0.808900	0.920423	0.864662
210	86	222	0.746548	0.877096	0.811822
139	86	147	0.860589	0.727811	0.794200
...	...	...	...	...	...
128	86	136	0.037854	0.047265	0.042560
150	86	158	0.066134	0.018647	0.042390
21	86	23	0.039235	0.035547	0.037391
46	86	50	0.033323	0.032130	0.032726
62	86	66	0.004820	0.053801	0.029311

260 rows × 5 columns

Looks like store 138 is the control store for store 86. Again, we will visualize this into a graph.

In [200]:

```
trial_store = 86
control_store = 138

measure_over_time = data_metrics_pre.copy()
measure_over_time["STORE_NBR"] = measure_over_time["STORE_NBR"].apply(updateStores)
measure_over_time["STORE_TYPE"].unique()

pastSales = measure_over_time.groupby(["STORE_TYPE", "Month_ID"]).agg("mean")["tot_sales"].reset_index
()
pastSales["Month_ID"] = pastSales["Month_ID"].astype(str).str.replace("-", "").astype(float)

pastCust = measure_over_time.groupby(["STORE_TYPE", "Month_ID"]).agg("mean")["num_customer"].reset_ind
ex()
pastCust["Month_ID"] = pastCust["Month_ID"].astype(str).str.replace("-", "").astype(float)
pastCust
```

Out[200]:

	STORE_TYPE	Month_ID	num_customer
0	Control	201807.0	54.000000
1	Control	201808.0	50.000000
2	Control	201809.0	45.000000
3	Control	201810.0	36.000000
4	Control	201811.0	41.000000
5	Control	201812.0	50.000000
6	Control	201901.0	35.000000
7	Others	201807.0	86.965116
8	Others	201808.0	86.418605
9	Others	201809.0	83.879845
10	Others	201810.0	86.011628
11	Others	201811.0	84.290698
12	Others	201812.0	88.062016
13	Others	201901.0	85.558140
14	Trial	201807.0	55.000000
15	Trial	201808.0	48.000000
16	Trial	201809.0	44.000000
17	Trial	201810.0	38.000000
18	Trial	201811.0	44.000000
19	Trial	201812.0	49.000000
20	Trial	201901.0	39.000000

In [183]:

```
fig = plt.figure(figsize=(10,15))
ax1 = fig.add_subplot(2,1,1)
ax2 = fig.add_subplot(2,1,2)
sns.lineplot(x=pastSales["Month_ID"], y=pastSales["tot_sales"], hue=pastSales["STORE_TYPE"], ax=ax1).s
et_title("Total Sales by Month")
sns.lineplot(x=pastCust["Month_ID"], y=pastCust["num_customer"], hue=pastCust["STORE_TYPE"], ax=ax2).s
et_title("Total Customers by Month")
```

Out[183]: Text(0.5, 1.0, 'Total Customers by Month')

Great, the trends for both Total sales and Total Customers are very similar. Next, less asses the impact of the trial on sales.

In [189]:

```
data_metrics_pre["Month_ID"] = data_metrics_pre["Month_ID"].astype(str).str.replace("-", "").astype(fl
oat)
trial_metrics = data_metrics_pre[(data_metrics_pre["STORE_NBR"] == trial_store) & (data_metrics_pre["M
onth_ID"] < 201902)]["tot_sales"]
control_metrics = data_metrics_pre[(data_metrics_pre["STORE_NBR"] == control_store) & (data_metrics_pr
e["Month_ID"] < 201902)]["tot_sales"]

scalingFactorForControlSales = trial_metrics.sum()/control_metrics.sum()

data_metrics_sales = data_metrics_fs.copy()
scaled_control_sales = data_metrics_sales[data_metrics_sales["STORE_NBR"] == control_store]
scaled_control_sales["controlSales"] = data_metrics_sales["tot_sales"]*scalingFactorForControlSales
scaled_control_sales = scaled_control_sales.drop(["num_customer", "tot_sales", "avg_transaction","avg_
chips","avg_price_per_quantity"], axis=1).reindex()

trial_df_totsales = data_metrics_fs[data_metrics_fs["STORE_NBR"] == trial_store].drop(["avg_transactio
n", "avg_chips", "avg_price_per_quantity", "num_customer"], axis=1)

percent_dif = trial_df_totsales.merge(scaled_control_sales, on=("Month_ID")).rename({"STORE_NBR_x": "T
RIAL", "STORE_NBR_y": "CONTROL"}, axis=1)
percent_dif = percent_dif[["TRIAL", "CONTROL", "Month_ID", "tot_sales", "controlSales"]]
percent_dif["percentage_difference"] = np.abs((percent_dif["tot_sales"] - percent_dif["controlSales"])
/((percent_dif["tot_sales"] + percent_dif["controlSales"])/2))
percent_dif

#Take standard deviation of percent difference
stdDev = percent_dif["percentage_difference"].std()

#There are 8 months in the pre-trial period so degrees of freedom = 8 - 1 = 7
degreesOfFreedom = 7

#We will test the null hypothesis being 0 difference between trial and control stores
percent_dif["tvalue"] = np.abs(percent_dif["percentage_difference"] - percent_dif["percentage_differen
ce"].mean())/stdDev

#Let's filter for the trial period
percent_trial = percent_dif[percent_dif["Month_ID"] > "2019-01"]
percent_trial
```

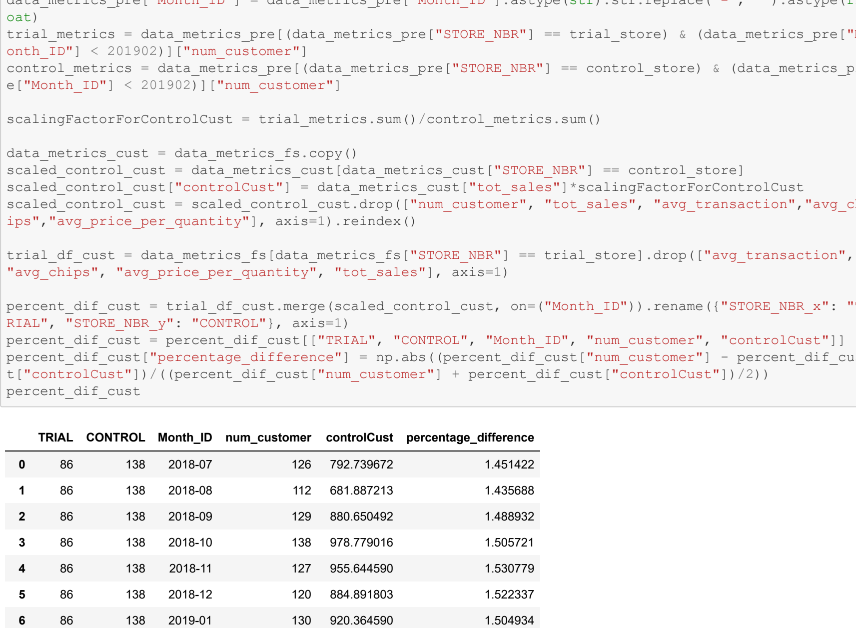
Out[189]:

	TRIAL	CONTROL	Month_ID	tot_sales	controlSales	percentage_difference	tvalue
7	86	138	2019-02	913.2	724.548428	0.230379	1.621266
8	86	138	2019-03	1026.8	910.379711	0.120196	0.193940
9	86	138	2019-04	848.2	807.398208	0.049289	0.724584
10	86	138	2019-05	889.3	805.656040	0.098697	0.084548
11	86	138	2019-06	838.0	1109.180468	0.278537	2.245101

In [190]:

```
measure_over_time_sales = data_metrics_fs[["STORE_NBR", "Month_ID", "tot_sales"]]
measure_over_time_sales["Month_ID"] = measure_over_time_sales["Month_ID"].astype(str).str.replace("-",
 "").astype(int)
measure_over_time_sales["STORE_NBR"] = measure_over_time_sales["STORE_NBR"].apply(updateStores)
measure_over_time_sales = measure_over_time_sales.rename({"STORE_NBR": "STORE_TYPE"}, axis=1)
measure_over_time_sales = measure_over_time_sales[measure_over_time_sales["STORE_TYPE"].isin(["Contro
l", "Trial"])]

#Control Store 95th Percentile
pastSales_control95 = measure_over_time_sales[measure_over_time_sales["STORE_TYPE"] == "Control"]
pastSales_control95["tot_sales"] = pastSales_control95["tot_sales"] * (1 + stdDev * 2)
pastSales_control95["STORE_TYPE"] = "Control 95th % confidence interval"
pastSales_control95

#Control Store 95th Percentile
pastSales_control5 = measure_over_time_sales[measure_over_time_sales["STORE_TYPE"] == "Control"]
pastSales_control5["tot_sales"] = pastSales_control5["tot_sales"] * (1 - stdDev * 2)
pastSales_control5["STORE_TYPE"] = "Control 5th % confidence interval"
pastSales_control5

trialAssesment = pd.concat([measure_over_time_sales, pastSales_control95, pastSales_control5])
trialAssesment
trialAssesment_month = trialAssesment[(trialAssesment["Month_ID"] > 201901) & (trialAssesment["Month_I
D"] < 201905)]
month_label = trialAssesment_month["Month_ID"].astype(str).unique()

#Plot into a graph
fig = plt.figure(figsize=(15,10))
ax1 = fig.add_subplot(1,1,1)
sns.lineplot(x="Month_ID", y="tot_sales", hue="STORE_TYPE", data=trialAssesment_month, ax=ax1).set_tit
le("Total Sales by Month")
```

Out[190]: Text(0.5, 1.0, 'Total Sales by Month')



It looks like the sales of trial store 86 are not very different from its control store; 2 of the 3 months are out of the 5th to 95th percentile. Let's take a look at the total customer now.

In [191]:

```
data_metrics_pre["Month_ID"] = data_metrics_pre["Month_ID"].astype(str).str.replace("-", "").astype(fl
oat)
trial_metrics = data_metrics_pre[(data_metrics_pre["STORE_NBR"] == trial_store) & (data_metrics_pre["M
onth_ID"] < 201902)]["num_customer"]
control_metrics = data_metrics_pre[(data_metrics_pre["STORE_NBR"] == control_store) & (data_metrics_pr
e["Month_ID"] < 201902)]["num_customer"]

scalingFactorForControlCust = trial_metrics.sum()/control_metrics.sum()

data_metrics_cust = data_metrics_fs.copy()
scaled_control_cust = data_metrics_cust[data_metrics_cust["STORE_NBR"] == control_store]
scaled_control_cust["controlCust"] = data_metrics_cust["tot_sales"]*scalingFactorForControlCust
scaled_control_cust = scaled_control_cust.drop(["num_customer", "tot_sales", "avg_transaction","avg_ch
ips","avg_price_per_quantity"], axis=1).reindex()

trial_df_cust = data_metrics_fs[data_metrics_fs["STORE_NBR"] == trial_store].drop(["avg_transaction",
"avg_chips", "avg_price_per_quantity", "tot_sales"], axis=1)

percent_dif_cust = trial_df_cust.merge(scaled_control_cust, on=("Month_ID")).rename({"STORE_NBR_x": "T
RIAL", "STORE_NBR_y": "CONTROL"}, axis=1)
percent_dif_cust = percent_dif_cust[["TRIAL", "CONTROL", "Month_ID", "num_customer", "controlCust"]]
percent_dif_cust["percentage_difference"] = np.abs((percent_dif_cust["num_customer"] - percent_dif_cus
t["controlCust"])/((percent_dif_cust["num_customer"] + percent_dif_cust["controlCust"])/2))
percent_dif_cust
```

Out[191]:

	TRIAL	CONTROL	Month_ID	num_customer	controlCust	percentage_difference
0	86	138	2018-07	126	792.739672	1.451422
1	86	138	2018-08	112	681.887213	1.435688
2	86	138	2018-09	129	880.650492	1.488932
3	86	138	2018-10	138	978.779016	1.505721
4	86	138	2018-11	127	955.644590	1.530779
5	86	138	2018-12	120	884.891803	1.522337
6	86	138	2019-01	130	920.364590	1.504934
7	86	138	2019-02	139	721.601311	1.353940
8	86	138	2019-03	142	906.676721	1.458365
9	86	138	2019-04	127	804.114098	1.454417
10	86	138	2019-05	129	802.379016	1.445983
11	86	138	2019-06	119	1104.668852	1.611006

In [192]:

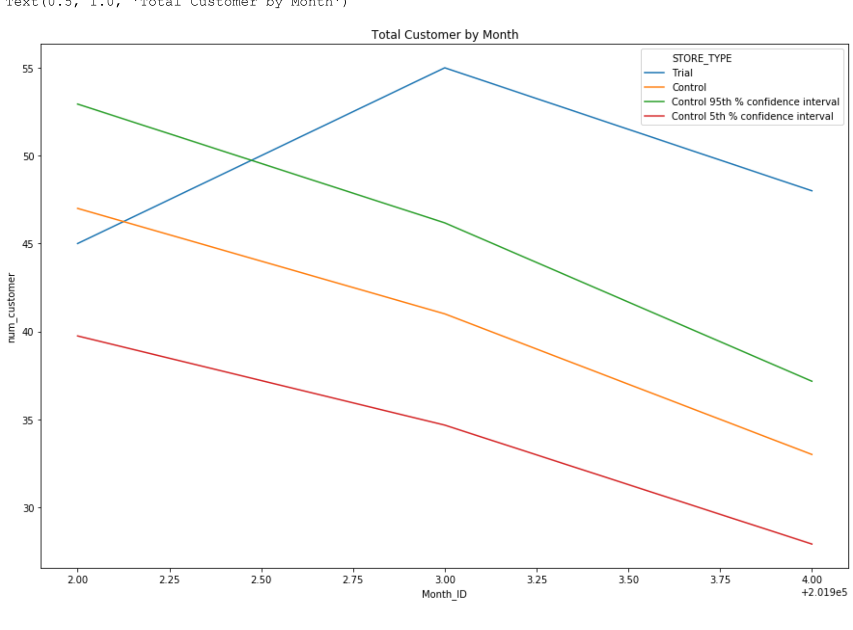
```
#Take standard deviation of percentage difference
stdDev_cust = percent_dif_cust["percentage_difference"].std()

#There are 8 months in the pre-trial period so degrees of freedom = 8 - 1 = 7
degreesOfFreedom = 7

#We will test the null hypothesis being 0 difference between trial and control stores
percent_dif_cust["tvalue"] = np.abs(percent_dif_cust["percentage_difference"] - percent_dif_cust["perc
entage_difference"].mean())/stdDev

#Let's filter for the trial period
percent_trial = percent_dif_cust[percent_dif_cust["Month_ID"] > "2019-01"]
percent_trial
```

Out[192]:

	TRIAL	CONTROL	Month_ID	num_customer	controlCust	percentage_difference	tvalue
7	86	138	2019-02	139	721.601311	1.353940	1.636794
8	86	138	2019-03	142	906.676721	1.458365	0.284065
9	86	138	2019-04	127	804.114098	1.454417	0.335208
10	86	138	2019-05	129	802.379016	1.445983	0.444465
11	86	138	2019-06	119	1104.668852	1.611006	1.693256

```
In [193]: measure_over_time_cust = data_metrics_fs[["STORE_NBR", "Month_ID", "num_customer"]]
measure_over_time_cust["Month_ID"] = measure_over_time_cust["Month_ID"].astype(str).str.replace("-",
"").astype(int)
measure_over_time_cust["STORE_NBR"] = measure_over_time_cust["STORE_NBR"].apply(updateStores)
measure_over_time_cust = measure_over_time_cust.rename({"STORE_NBR": "STORE_TYPE"}, axis=1)
measure_over_time_cust = measure_over_time_cust[measure_over_time_cust["STORE_TYPE"].isin(["Control",
"Trial"])]

#Control Store 95th Percentile
pastCust_control95 = measure_over_time_cust[measure_over_time_cust["STORE_TYPE"] == "Control"]
pastCust_control95["num_customer"] = pastCust_control95["num_customer"] * (1 + stdDev_cust * 2)
pastCust_control95["STORE_TYPE"] = "Control 95th % confidence interval"
pastCust_control95

#Control Store 95th Percentile
pastCust_control5 = measure_over_time_cust[measure_over_time_cust["STORE_TYPE"] == "Control"]
pastCust_control5["num_customer"] = pastCust_control5["num_customer"] * (1 - stdDev * 2)
pastCust_control5["STORE_TYPE"] = "Control 5th % confidence interval"
pastCust_control5

trialAssesment = pd.concat([measure_over_time_cust, pastCust_control95, pastCust_control5])
trialAssesment
trialAssesment_month = trialAssesment[(trialAssesment["Month_ID"] > 201901) & (trialAssesment["Month_I
D"] < 201905)]
month_label = trialAssesment_month["Month_ID"].astype(str).unique()

#Plot into a graph
fig = plt.figure(figsize=(15,10))
ax1 = fig.add_subplot(1,1,1)
sns.lineplot(x="Month_ID", y="num_customer", hue="STORE_TYPE", data=trialAssesment_month, ax=ax1).set_
title("Total Customer by Month")
```

```
Out[193]: Text(0.5, 1.0, 'Total Customer by Month')
```



It seems like the number of customers is significantly higher in 2 out of the 3 months. It suggest that there is a significant impact on increasing the number of customers in trial store 86. The increase in number of customers is way higher than the increase in sales. However, as we saw, the sales were not significantly higher. This might be due to special deals in trial store which might result in lower prices, impacting the results. Let's perform the same assesments for trial store 88

Trial Store 88

```
In [198]: trial_store = 88
corr_nSales = CalculateCorrelation(data_metrics_pre, "tot_sales", trial_store)
magnitude_nSales = CalculateMagnitudeDistance(data_metrics_pre, "tot_sales", trial_store)
corr_nCustomer = CalculateCorrelation(data_metrics_pre, "num_customer", trial_store)
magnitude_nCustomer = CalculateMagnitudeDistance(data_metrics_pre, "num_customer", trial_store)

score_nSales = corr_nSales.merge(magnitude_nSales, on=["STORE1", "STORE2"])
score_nSales = score_nSales.rename({"tot_sales": "MAGNITUDESALES"}, axis=1)
score_nSales["scoreNSales"] = (0.5*score_nSales["COORMEASURE"] + 0.5*score_nSales["MAGNITUDESALES"])

score_nCust = corr_nCustomer.merge(magnitude_nCustomer, on=["STORE1", "STORE2"])
score_nCust = score_nCust.rename({"num_customer": "MAGNITUDECUST"}, axis=1)
score_nCust["scoreNCust"] = (0.5*score_nCust["COORMEASURE"] + 0.5*score_nCust["MAGNITUDECUST"])

score_control = score_nCust.merge(score_nSales, on=["STORE1", "STORE2"])
score_control = score_control.drop(["COORMEASURE_x", "MAGNITUDECUST", "COORMEASURE_y", "MAGNITUDESALE
S"], axis=1)
score_control["finalControlScore"] = np.abs(score_control["scoreNSales"] * 0.5 + score_control["scoreN
Cust"] * 0.5)
score_control.sort_values(by="finalControlScore", ascending=False)
```

Out[198]:

	STORE1	STORE2	scoreNCust	scoreNSales	finalControlScore
82	88	88	1.000000	1.000000	1.000000
6	88	7	0.865827	0.713819	0.789823
115	88	123	0.889912	0.627976	0.758944
170	88	178	0.767809	0.713855	0.740832
194	88	203	0.729727	0.729388	0.729558
...	...	...	...	...	...
231	88	243	-0.106289	0.095223	0.005533
79	88	84	0.019109	-0.008622	0.005244
70	88	74	0.013400	-0.018047	0.002324
69	88	73	0.037965	-0.034092	0.001936
125	88	133	-0.001144	0.002625	0.000740

260 rows × 5 columns

Store 7 will be our control store for trial 88.

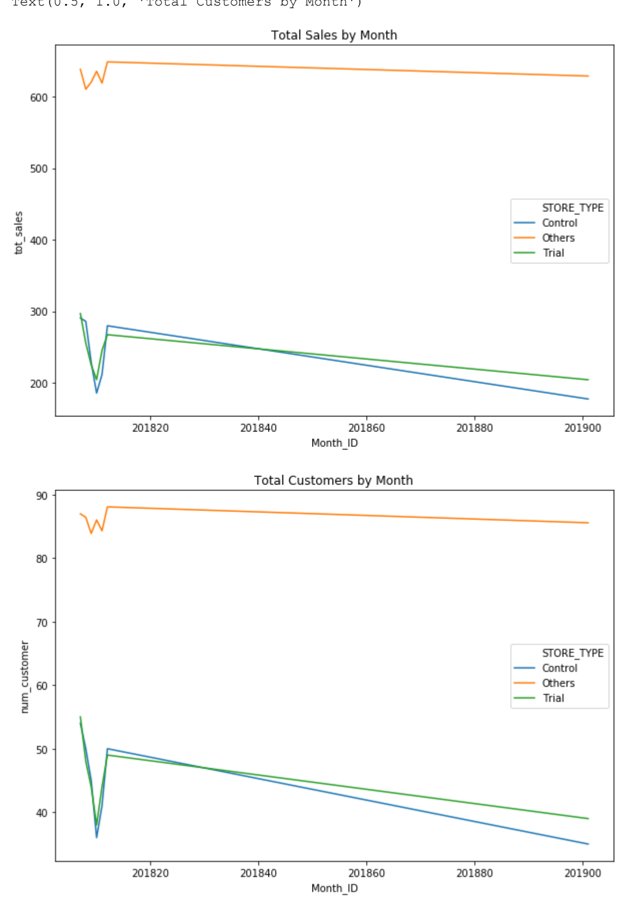
```
In [201]: trial_store = 88
control_store = 7

measure_over_time = data_metrics_pre.copy()
measure_over_time["STORE_TYPE"] = measure_over_time["STORE_NBR"].apply(updateStores)
measure_over_time["STORE_TYPE"].unique()

pastSales = measure_over_time.groupby(["STORE_TYPE", "Month_ID"]).agg("mean")["tot_sales"].reset_index
()
pastSales["Month_ID"] = pastSales["Month_ID"].astype(str).str.replace("-", "").astype(float)

pastCust = measure_over_time.groupby(["STORE_TYPE", "Month_ID"]).agg("mean")["num_customer"].reset_ind
ex()
pastCust["Month_ID"] = pastCust["Month_ID"].astype(str).str.replace("-", "").astype(float)
pastCust
```

Out[201]:

	STORE_TYPE	Month_ID	num_customer
0	Control	201807.0	54.000000
1	Control	201808.0	50.000000
2	Control	201809.0	45.000000
3	Control	201810.0	36.000000
4	Control	201811.0	41.000000
5	Control	201812.0	50.000000
6	Control	201901.0	35.000000
7	Others	201807.0	86.965116
8	Others	201808.0	86.418605
9	Others	201809.0	83.879845
10	Others	201810.0	86.011628
11	Others	201811.0	84.290698
12	Others	201812.0	88.062016
13	Others	201901.0	85.558140
14	Trial	201807.0	55.000000
15	Trial	201808.0	48.000000
16	Trial	201809.0	44.000000
17	Trial	201810.0	38.000000
18	Trial	201811.0	44.000000
19	Trial	201812.0	49.000000
20	Trial	201901.0	39.000000

```
In [202]: fig = plt.figure(figsize=(10,15))
ax1 = fig.add_subplot(2,1,1)
ax2 = fig.add_subplot(2,1,2)
sns.lineplot(x=pastSales["Month_ID"], y=pastSales["tot_sales"], hue=pastSales["STORE_TYPE"], ax=ax1).s
et_title("Total Sales by Month")
sns.lineplot(x=pastCust["Month_ID"], y=pastCust["num_customer"], hue=pastCust["STORE_TYPE"], ax=ax2).s
et_title("Total Customers by Month")
```

```
Out[202]: Text(0.5, 1.0, 'Total Customers by Month')
```



The trends between total sales and total customers are very similar which means that store 7 is a suiable control store. Let's asses the impact of the trial on sales

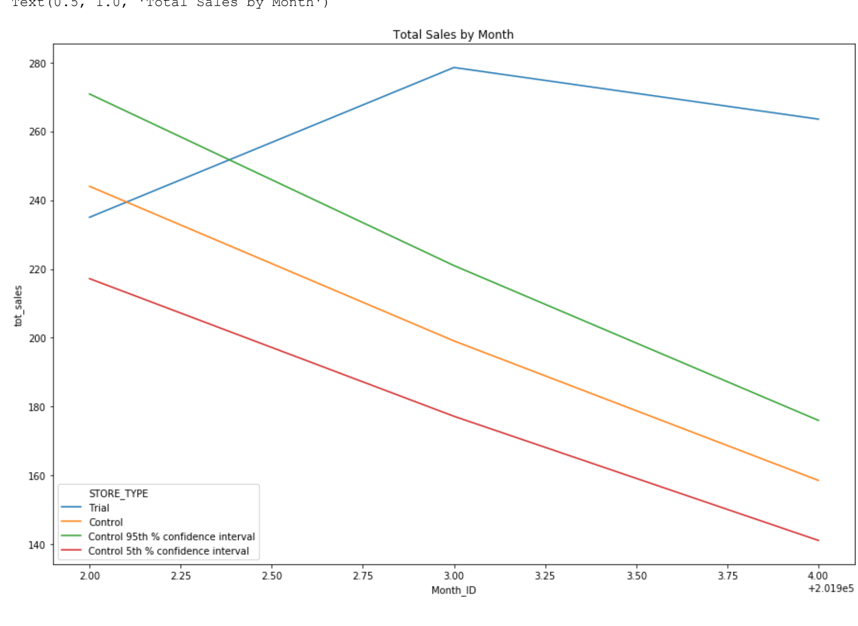
```
In [203]: data_metrics_pre["Month_ID"] = data_metrics_pre["Month_ID"].astype(str).str.replace("-", "").astype(fl
oat)
trial_metrics = data_metrics_pre[(data_metrics_pre["STORE_NBR"] == trial_store) & (data_metrics_pre["M
onth_ID"] < 201902)]["tot_sales"]
control_metrics = data_metrics_pre[(data_metrics_pre["STORE_NBR"] == control_store) & (data_metrics_pr
e["Month_ID"] < 201902)]["tot_sales"]

scalingFactorForControlSales = trial_metrics.sum()/control_metrics.sum()

data_metrics_sales = data_metrics_fs.copy()
scaled_control_sales = data_metrics_sales[data_metrics_sales["STORE_NBR"] == control_store]
scaled_control_sales["controlSales"] = data_metrics_sales["tot_sales"]*scalingFactorForControlSales
scaled_control_sales = scaled_control_sales.drop(["num_customer", "tot_sales", "avg_transaction","avg_
chips","avg_price_per_quantity"], axis=1).reindex()

trial_df_totsales = data_metrics_fs[data_metrics_fs["STORE_NBR"] == trial_store].drop(["avg_transactio
n", "avg_chips", "avg_price_per_quantity", "num_customer"], axis=1)

percent_dif = trial_df_totsales.merge(scaled_control_sales, on=("Month_ID")).rename({"STORE_NBR_x": "T
RIAL", "STORE_NBR_y": "CONTROL"}, axis=1)
percent_dif = percent_dif[["TRIAL", "CONTROL", "Month_ID", "tot_sales", "controlSales"]]
percent_dif["percentage_difference"] = np.abs((percent_dif["tot_sales"] - percent_dif["controlSales"])
/((percent_dif["tot_sales"] + percent_dif["controlSales"])/2))
percent_dif

#Take standard deviation of percent difference
stdDev = percent_dif["percentage_difference"].std()

#There are 8 months in the pre-trial period so degrees of freedom = 8 - 1 = 7
degreesOfFreedom = 7

#We will test the null hypothesis being 0 difference between trial and control stores
percent_dif["tvalue"] = np.abs(percent_dif["percentage_difference"] - percent_dif["percentage_differen
ce"].mean())/stdDev

#Let's filter for the trial period
percent_trial = percent_dif[percent_dif["Month_ID"] > "2019-01"]
percent_trial
```

Out[203]:

	TRIAL	CONTROL	Month_ID	tot_sales	controlSales	percentage_difference	tvalue
7	88	7	2019-02	1370.20	1316.924460	0.039652	0.147949
8	88	7	2019-03	1477.20	1470.120856	0.004804	0.782273
9	88	7	2019-04	1439.40	1209.148101	0.173870	2.295118
10	88	7	2019-05	1308.25	1243.533892	0.050722	0.053547
11	88	7	2019-06	1354.60	1398.013340	0.031543	0.295552

```
In [204]: measure_over_time_sales = data_metrics_fs[["STORE_NBR", "Month_ID", "tot_sales"]]
measure_over_time_sales["Month_ID"] = measure_over_time_sales["Month_ID"].astype(str).str.replace("-",
"").astype(int)
measure_over_time_sales["STORE_NBR"] = measure_over_time_sales["STORE_NBR"].apply(updateStores)
measure_over_time_sales = measure_over_time_sales.rename({"STORE_NBR": "STORE_TYPE"}, axis=1)
measure_over_time_sales = measure_over_time_sales[measure_over_time_sales["STORE_TYPE"].isin(["Contro
l", "Trial"])]

#Control Store 95th Percentile
pastSales_control95 = measure_over_time_sales[measure_over_time_sales["STORE_TYPE"] == "Control"]
pastSales_control95["tot_sales"] = pastSales_control95["tot_sales"] * (1 + stdDev * 2)
pastSales_control95["STORE_TYPE"] = "Control 95th % confidence interval"
pastSales_control95

#Control Store 95th Percentile
pastSales_control5 = measure_over_time_sales[measure_over_time_sales["STORE_TYPE"] == "Control"]
pastSales_control5["tot_sales"] = pastSales_control5["tot_sales"] * (1 - stdDev * 2)
pastSales_control5["STORE_TYPE"] = "Control 5th % confidence interval"
pastSales_control5

trialAssesment = pd.concat([measure_over_time_sales, pastSales_control95, pastSales_control5])
trialAssesment
trialAssesment_month = trialAssesment[(trialAssesment["Month_ID"] > 201901) & (trialAssesment["Month_I
D"] < 201905)]
month_label = trialAssesment_month["Month_ID"].astype(str).unique()

#Plot into a graph
fig = plt.figure(figsize=(15,10))
ax1 = fig.add_subplot(1,1,1)
sns.lineplot(x="Month_ID", y="tot_sales", hue="STORE_TYPE", data=trialAssesment_month, ax=ax1).set_tit
le("Total Sales by Month")
```

```
Out[204]: Text(0.5, 1.0, 'Total Sales by Month')
```



The results show that the trial in store 88 is significantly different to its control store in the trial period since in 2 out of 3 months, the trial store lies above the 5% and 95% line. Let's look at customer as well.

```
In [205]: data_metrics_pre["Month_ID"] = data_metrics_pre["Month_ID"].astype(str).str.replace("-", "").astype(fl
oat)
trial_metrics = data_metrics_pre[(data_metrics_pre["STORE_NBR"] == trial_store) & (data_metrics_pre["M
onth_ID"] < 201902)]["num_customer"]
control_metrics = data_metrics_pre[(data_metrics_pre["STORE_NBR"] == control_store) & (data_metrics_pr
e["Month_ID"] < 201902)]["num_customer"]

scalingFactorForControlCust = trial_metrics.sum()/control_metrics.sum()

data_metrics_cust = data_metrics_fs.copy()
scaled_control_cust = data_metrics_cust[data_metrics_cust["STORE_NBR"] == control_store]
scaled_control_cust["controlCust"] = data_metrics_cust["tot_sales"]*scalingFactorForControlCust
scaled_control_cust = scaled_control_cust.drop(["num_customer", "tot_sales", "avg_transaction","avg_ch
ips","avg_price_per_quantity"], axis=1).reindex()

trial_df_cust = data_metrics_fs[data_metrics_fs["STORE_NBR"] == trial_store].drop(["avg_transaction",
"avg_chips", "avg_price_per_quantity", "tot_sales"], axis=1)

percent_dif_cust = trial_df_cust.merge(scaled_control_cust, on=("Month_ID")).rename({"STORE_NBR_x": "T
RIAL", "STORE_NBR_y": "CONTROL"}, axis=1)
percent_dif_cust = percent_dif_cust[["TRIAL", "CONTROL", "Month_ID", "num_customer", "controlCust"]]
percent_dif_cust["percentage_difference"] = np.abs((percent_dif_cust["num_customer"] - percent_dif_cus
t["controlCust"])/((percent_dif_cust["num_customer"] + percent_dif_cust["controlCust"])/2))
percent_dif_cust
```

Out[205]:

	TRIAL	CONTROL	Month_ID	num_customer	controlCust	percentage_difference
0	88	7	2018-07	153	1287.718235	1.575212
1	88	7	2018-08	160	1407.354007	1.591669
2	88	7	2018-09	159	1441.786992	1.602695
3	88	7	2018-10	158	1336.980023	1.577252
4	88	7	2018-11	157	1352.814170	1.584055
5	88	7	2018-12	149	1138.676190	1.537151
6	88	7	2019-01	146	1225.386992	1.574154
7	88	7	2019-02	154	1289.854588	1.573364
8	88	7	2019-03	170	1439.901974	1.577614
9	88	7	2019-04	162	1184.293612	1.518679
10	88	7	2019-05	155	1217.972590	1.548425
11	88	7	2019-06	150	1369.276655	1.605075

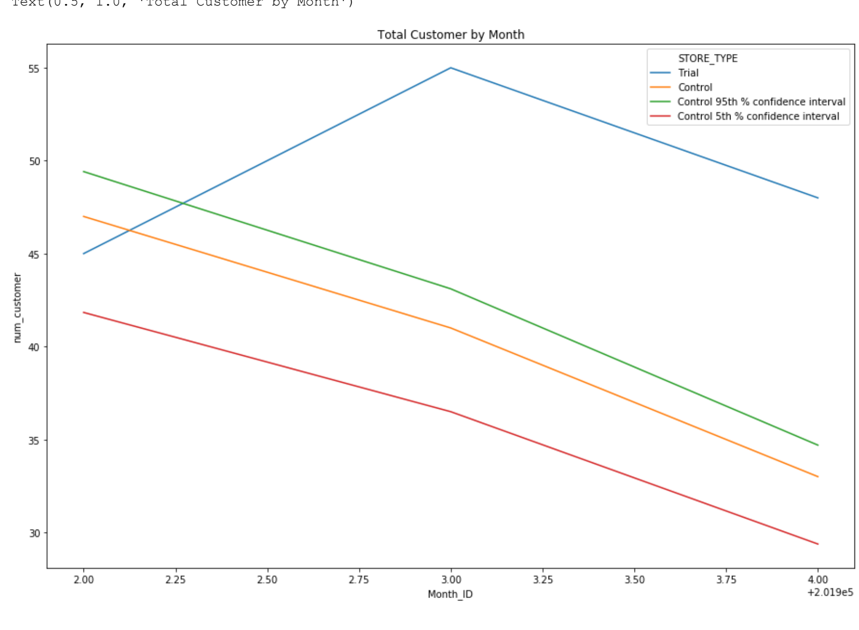
```
In [206]: #Take standard deviation of percentage difference
stdDev_cust = percent_dif_cust["percentage_difference"].std()

#There are 8 months in the pre-trial period so degrees of freedom = 8 - 1 = 7
degreesOfFreedom = 7

#We will test the null hypothesis being 0 difference between trial and control stores
percent_dif_cust["tvalue"] = np.abs(percent_dif_cust["percentage_difference"] - percent_dif_cust["perc
entage_difference"].mean())/stdDev

#Let's filter for the trial period
percent_trial = percent_dif_cust[percent_dif_cust["Month_ID"] > "2019-01"]
percent_trial
```

Out[206]:

	TRIAL	CONTROL	Month_ID	num_customer	controlCust	percentage_difference	tvalue
7	88	7	2019-02	154	1289.854588	1.573364	0.022794
8	88	7	2019-03	170	1439.901974	1.577614	0.100149
9	88	7	2019-04	162	1184.293612	1.518679	0.972609
10	88	7	2019-05	155	1217.972590	1.548425	0.431155
11	88	7	2019-06	150	1369.276655	1.605075	0.600005

```
In [207]: measure_over_time_cust = data_metrics_fs[["STORE_NBR", "Month_ID", "num_customer"]]
measure_over_time_cust["Month_ID"] = measure_over_time_cust["Month_ID"].astype(str).str.replace("-",
"").astype(int)
measure_over_time_cust["STORE_NBR"] = measure_over_time_cust["STORE_NBR"].apply(updateStores)
measure_over_time_cust = measure_over_time_cust.rename({"STORE_NBR": "STORE_TYPE"}, axis=1)
measure_over_time_cust = measure_over_time_cust[measure_over_time_cust["STORE_TYPE"].isin(["Control",
"Trial"])]

#Control Store 95th Percentile
pastCust_control95 = measure_over_time_cust[measure_over_time_cust["STORE_TYPE"] == "Control"]
pastCust_control95["num_customer"] = pastCust_control95["num_customer"] * (1 + stdDev_cust * 2)
pastCust_control95["STORE_TYPE"] = "Control 95th % confidence interval"
pastCust_control95

#Control Store 95th Percentile
pastCust_control5 = measure_over_time_cust[measure_over_time_cust["STORE_TYPE"] == "Control"]
pastCust_control5["num_customer"] = pastCust_control5["num_customer"] * (1 - stdDev * 2)
pastCust_control5["STORE_TYPE"] = "Control 5th % confidence interval"
pastCust_control5

trialAssesment = pd.concat([measure_over_time_cust, pastCust_control95, pastCust_control5])
trialAssesment
trialAssesment_month = trialAssesment[(trialAssesment["Month_ID"] > 201901) & (trialAssesment["Month_I
D"] < 201905)]
month_label = trialAssesment_month["Month_ID"].astype(str).unique()

#Plot into a graph
fig = plt.figure(figsize=(15,10))
ax1 = fig.add_subplot(1,1,1)
sns.lineplot(x="Month_ID", y="num_customer", hue="STORE_TYPE", data=trialAssesment_month, ax=ax1).set_
title("Total Customer by Month")
```

```
Out[207]: Text(0.5, 1.0, 'Total Customer by Month')
```



The results show that there is significant impact in the trial store for at least 2 out of the 3 months. This indicates a positive trial effect.

Conclusion

Through this analysis, we've found control stores 233, 138, and 7 for trial store 77, 86 and 88 respectively.

The results for 77 and 88 during the trial period show a significant difference in at least two out of 3 months. However, this is not the case for trial store 86. We can check with the client whether the implementation of the trial was different in store 86 but overall, the trial store shows significant increase in sales.