Task 2-Experimentation and Uplift testing

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

This can be broken down by:

total sales revenue

total number of customers

average number of transactions per customer

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

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

Main areas of Focus are :

Select control stores – Explore data, define metrics, visualize graphs

Assessment of the trial – insights/trends by comparing trial stores with control stores

Collate findings – summarize and provide recommendations

import pandas as pd

import matplotlib.pyplot as plt

%matplotlib inline

In [1] : import numpy as np

data = pd.read_csv(r"C:\Users\indup\Downloads\QVI_data.csv")

In [2] : data.head()

OUT [2] :LYLTY_CARD_NBR DATE STORE_ID TXN_ID PROD_NBR PROD_NAME PROD_QTY

0 1000 2018-10-17 1 1 5 Natural Chip Compny

SeaSalt175g 2

1 1002 2018-09-16 1 2 58 Red Rock Deli Chikn&

Garlic Aioli 150g 1

2 1003 2019-03-07 1 3 52 Grain Waves Sour

Cream&Chives 210G 1

3 1003 2019-03-08 1 4 106 Natural ChipCo Hony

Soy Chckn175g 1

4 1004 2018-11-02 1 5 96 WW Original Stacked

Chips 160g 1

TOT_SALES PACK_SIZE BRAND LIFESTAGE PREMIUM_CUSTOMER

6.0 175 NATURAL YOUNG SINGLES/ COUPLES Premium

2.7 150 RRD YOUNG SINGLES/ COUPLES Mainstream

3.6 210 GRNWVES YOUNG FAMILIES Budget

3.0 175 NATURAL YOUNG FAMILIES Budget

1.9 160 WOOL

WORTHS OLDER SINGLES/COUPLES Mainstream

In [3] : 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 [4] : data["DATE"] = pd.to_datetime(data["DATE"])

data["YEARMONTH"] = data["DATE"].dt.strftime("%Y%m").astype("int")

Compile each store's monthly:

1.Total sales

2.Number of customers,

3.Average transactions per customer

4.Average chips per customer

5.Average price per unit

In [5] : def monthly_store_metrics():

```
    store_yrmo_group = qvi.groupby(["STORE_NBR", "YEARMONTH"])
    total = store_yrmo_group["TOT_SALES"].sum()
    num_cust = store_yrmo_group["LYLTY_CARD_NBR"].nunique()
    trans_per_cust = store_yrmo_group.size() / num_cust
    avg_chips_per_cust = store_yrmo_group["PROD_QTY"].sum() / num_cust
    avg_chips_price = total / store_yrmo_group["PROD_QTY"].sum()
    aggregates = [total, num_cust, trans_per_cust, avg_chips_per_cust, avg_chips_price]
```

metrics = pd.concat(aggregates, axis=1)

metrics.columns = ["TOT_SALES", "nCustomers", "nTxnPerCust", "nChipsPerTxn", "avgPricePerUnit"]

return metrics

In [6] : data_monthly_metrics = monthly_store_metrics().reset_index()

data_monthly_metrics.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3169 entries, 0 to 3168
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   STORE_NBR        3169 non-null   int64  
 1   YEARMONTH        3169 non-null   int64  
 2   TOT_SALES        3169 non-null   float64
 3   nCustomers       3169 non-null   int64  
 4   nTxnPerCust      3169 non-null   float64
 5   nChipsPerTxn     3169 non-null   float64
 6   avgPricePerUnit  3169 non-null   float64
dtypes: float64(4), int64(3)
memory usage: 173.4 KB
```

In [7] : observ_counts = qvi_monthly_metrics["STORE_NBR"].value_counts()

full_observ_index = observ_counts[observ_counts == 12].index

full_observ = qvi_monthly_metrics[qvi_monthly_metrics["STORE_NBR"].isin(full_observ_index)]

pretrial_full_observ =

full_observ[full_observ["YEARMONTH"] < 201902]

pretrial_full_observ.head(8)

Out[7]:

	STORE_NBR	YEARMONTH	TOT_SALES	nCustomers	nTxnPerCust	nChipsPerTxn	avgPricePerUnit
0	1	201807	206.9	49	1.061224	1.265306	3.337097
1	1	201808	176.1	42	1.023810	1.285714	3.261111
2	1	201809	278.8	59	1.050847	1.271186	3.717333
3	1	201810	188.1	44	1.022727	1.318182	3.243103
4	1	201811	192.6	46	1.021739	1.239130	3.378947
5	1	201812	189.6	42	1.119048	1.357143	3.326316
6	1	201901	154.8	35	1.028571	1.200000	3.685714
12	2	201807	150.8	39	1.051282	1.179487	3.278261

In [8] : def calcCorrTable(metricCol, storeComparison, inputTable=pretrial_full_observ):

  control_store_nbrs = inputTable[~inputTable["STORE_NBR"].isin([77, 86, 88])]["STORE_NBR"].unique()

  corrs = pd.DataFrame(columns = ["YEARMONTH", "Trial_Str", "Ctrl_Str", "Corr_Score"])

  trial_store = inputTable[inputTable["STORE_NBR"] == storeComparison][metricCol].reset_index()

  for control in control_store_nbrs:

    concat_df = pd.DataFrame(columns = ["YEARMONTH", "Trial_Str", "Ctrl_Str", "Corr_Score"])

    control_store = inputTable[inputTable["STORE_NBR"] ==

```
control][metricCol].reset_index()
    concat_df["Corr_Score"] = trial_store.corrwith(control_store, axis=1)
    concat_df["Trial_Str"] = storeComparison
    concat_df["Ctrl_Str"] = control
    concat_df["YEARMONTH"] = list(inputTable[inputTable["STORE_NBR"] == storeComparison]["YEARMONTH"])
    corrs = pd.concat([corrs, concat_df])
  return corrs
```

In [12] :

```
corr_table = pd.DataFrame()
for trial_num in [77, 86, 88]:
    corr_table = pd.concat([corr_table, calcCorrTable(["TOT_SALES", "nCustomers", "nTxnPerCust", "nChipsPerTxn", "avgPricePerUnit"], trial_num)])
corr_table.head(8)
```

Out[12]:

	YEARMONTH	Trial_Str	Ctrl_Str	Corr_Score
0	201807	77	1	0.070414
1	201808	77	1	0.027276
2	201809	77	1	0.002389
3	201810	77	1	-0.020045
4	201811	77	1	0.030024
5	201812	77	1	0.063946
6	201901	77	1	0.001470
0	201807	77	2	0.142957

In [13] : def calculateMagnitudeDistance(metricCol, storeComparison, inputTable=pretrial_full_observ):

    control_store_nbrs = inputTable[~inputTable["STORE_NBR"].isin([77, 86, 88])]["STORE_NBR"].unique()

    dists = pd.DataFrame()

    trial_store = inputTable[inputTable["STORE_NBR"] == storeComparison][metricCol]

    for control in control_store_nbrs:

        concat_df = abs(inputTable[inputTable["STORE_NBR"] == storeComparison].reset_index()[metricCol] - inputTable[inputTable["STORE_NBR"] == control].reset_index()[metricCol])

        concat_df["YEARMONTH"] =

```
list(inputTable[inputTable["STORE_NBR"] ==
storeComparison]["YEARMONTH"])
        concat_df["Trial_Str"] = storeComparison
        concat_df["Ctrl_Str"] = control
        dists = pd.concat([dists, concat_df])
    for col in metricCol:
        dists[col] = 1 - ((dists[col] - dists[col].min()) /
(dists[col].max() - dists[col].min()))
    dists["magnitude"] = dists[metricCol].mean(axis=1)
    return dists
```

In [14] : dist_table = pd.DataFrame()

```
for trial_num in [77, 86, 88]:
    dist_table = pd.concat([dist_table,
calculateMagnitudeDistance(["TOT_SALES", "nCustomers",
"nTxnPerCust", "nChipsPerTxn", "avgPricePerUnit"],
trial_num)])


dist_table.head(8)
dist_table
```

Out[14]:

	TOT_SALES	nCustomers	nTxnPerCust	nChipsPerTxn	avgPricePerUnit	YEARMONTH	Trial_Str	Ctrl_Str	magnitude
0	0.935431	0.980769	0.958035	0.739412	0.883569	201807	77	1	0.899443
1	0.942972	0.951923	0.993823	0.802894	0.886328	201808	77	1	0.915588
2	0.961503	0.836538	0.992126	0.730041	0.703027	201809	77	1	0.844647
3	0.988221	0.932692	0.989514	0.940460	0.590528	201810	77	1	0.888283
4	0.962149	0.951923	0.874566	0.730358	0.832481	201811	77	1	0.870296
...	...	...	...	...	...	...	...	...	...
2	0.207554	0.286822	0.462846	0.779879	0.923887	201809	88	272	0.532198
3	0.346797	0.387597	0.571497	0.796875	0.971133	201810	88	272	0.614780
4	0.286706	0.310078	0.623883	0.813241	0.966999	201811	88	272	0.600181
5	0.347151	0.387597	0.376456	0.699748	0.962198	201812	88	272	0.554630
6	0.402353	0.449612	0.450378	0.739714	0.971335	201901	88	272	0.602678

5397 rows × 9 columns

We'll select control stores based on how similar monthly total sales in dollar amounts and monthly number of customers are to the trial stores by using correlation and magnitude distance.

In [15] : def combine_corr_dist(metricCol, storeComparison, inputTable=pretrial_full_observ):

corrs = calcCorrTable(metricCol, storeComparison, inputTable)

dists = calculateMagnitudeDistance(metricCol, storeComparison, inputTable)

dists = dists.drop(metricCol, axis=1)

combine = pd.merge(corrs, dists, on=["YEARMONTH", "Trial_Str", "Ctrl_Str"])

return combine

In [16] : compare_metrics_table1 = pd.DataFrame()

for trial_num in [77, 86, 88]:

    compare_metrics_table1 = pd.concat([compare_metrics_table1, combine_corr_dist(["TOT_SALES"], trial_num)])

In [17] : corr_weight = 0.5

dist_weight = 1 - corr_weight

Determining the top five highest composite score for each trial based on Total sales

In [18] : grouped_comparison_table1 = compare_metrics_table1.groupby(["Trial_Str", "Ctrl_Str"]).mean().reset_index()

grouped_comparison_table1["CompScore"] = (corr_weight * grouped_comparison_table1["Corr_Score"]) + (dist_weight * grouped_comparison_table1["magnitude"])

for trial_num in compare_metrics_table1["Trial_Str"].unique():

print(grouped_comparison_table1[grouped_comparison_table1["Trial_Str"] == trial_num].sort_values(ascending=False, by="CompScore").head(), '\n')

	Trial_Str	Ctrl_Str	Corr_Score	magnitude	CompScore
218	77	233	1.0	0.986477	0.993238
239	77	255	1.0	0.979479	0.989739
177	77	188	1.0	0.977663	0.988831
49	77	53	1.0	0.976678	0.988339
120	77	131	1.0	0.976267	0.988134

	Trial_Str	Ctrl_Str	Corr_Score	magnitude	CompScore
356	86	109	1.0	0.966783	0.983391
401	86	155	1.0	0.965876	0.982938
464	86	222	1.0	0.962280	0.981140
467	86	225	1.0	0.960512	0.980256
471	86	229	1.0	0.951704	0.975852

	Trial_Str	Ctrl_Str	Corr_Score	magnitude	CompScore
551	88	40	1.0	0.941165	0.970582
538	88	26	1.0	0.904377	0.952189
582	88	72	1.0	0.903800	0.951900
517	88	4	1.0	0.903466	0.951733
568	88	58	1.0	0.891678	0.945839

In [19] : compare_metrics_table2 = pd.DataFrame()

for trial_num in [77, 86, 88]:

compare_metrics_table2 = pd.concat([compare_metrics_table2, combine_corr_dist(["nCustomers"], trial_num)])

Determining the top five highest composite score for each trial based on no. of customers

In [20] : grouped_comparison_table2 = compare_metrics_table2.groupby(["Trial_Str", "Ctrl_Str"]).mean().reset_index()

grouped_comparison_table2["CompScore"] = (corr_weight * grouped_comparison_table2["Corr_Score"]) + (dist_weight * grouped_comparison_table2["magnitude"])

for trial_num in compare_metrics_table2["Trial_Str"].unique():

print(grouped_comparison_table2[grouped_comparison_table2["Trial_Str"] == trial_num].sort_values(ascending=False, by="CompScore").head(), '\n')

	Trial_Str	Ctrl_Str	Corr_Score	magnitude	CompScore
218	77	233	1.0	0.993132	0.996566
38	77	41	1.0	0.976648	0.988324
101	77	111	1.0	0.968407	0.984203
105	77	115	1.0	0.967033	0.983516
15	77	17	1.0	0.965659	0.982830

	Trial_Str	Ctrl_Str	Corr_Score	magnitude	CompScore
401	86	155	1.0	0.986772	0.993386
467	86	225	1.0	0.969577	0.984788
356	86	109	1.0	0.969577	0.984788
471	86	229	1.0	0.964286	0.982143
293	86	39	1.0	0.961640	0.980820

	Trial_Str	Ctrl_Str	Corr_Score	magnitude	CompScore
736	88	237	1.0	0.987818	0.993909
705	88	203	1.0	0.944629	0.972315
551	88	40	1.0	0.942414	0.971207
668	88	165	1.0	0.935770	0.967885
701	88	199	1.0	0.932447	0.966224

In [21] : for trial_num in compare_metrics_table2["Trial_Str"].unique():

a = grouped_comparison_table1[grouped_comparison_table1["Trial

_Str"] == trial_num].sort_values(ascending=False, by="CompScore").set_index(["Trial_Str", "Ctrl_Str"])["CompScore"]

b = grouped_comparison_table2[grouped_comparison_table2["Trial_Str"] == trial_num].sort_values(ascending=False, by="CompScore").set_index(["Trial_Str", "Ctrl_Str"])["CompScore"]

print((pd.concat([a,b], axis=1).sum(axis=1)/2).sort_values(ascending=False).head(3), '\n')

```
Trial_Str  Ctrl_Str
77         233         0.994902
           41          0.986020
           46          0.984762
dtype: float64

Trial_Str  Ctrl_Str
86         155         0.988162
           109         0.984090
           225         0.982522
dtype: float64

Trial_Str  Ctrl_Str
88         40          0.970895
           26          0.958929
           72          0.954079
dtype: float64
```

Similarities based on total sales:

1.Trial store 77: Store 233, 255, 188

2.Trial store 86: Store 109, 155, 222

3.Trial store 88: Store 40, 26, 72

Similarities based on No. of Customers:

1.Trial store 77: Store 233, 41, 111

2.Trial store 86: Store 155, 225, 109

3.Trial store 88: Store 237, 203, 40

Final SImilarities based on Highest average of both features combined:

1.Trial store 77: Store 233

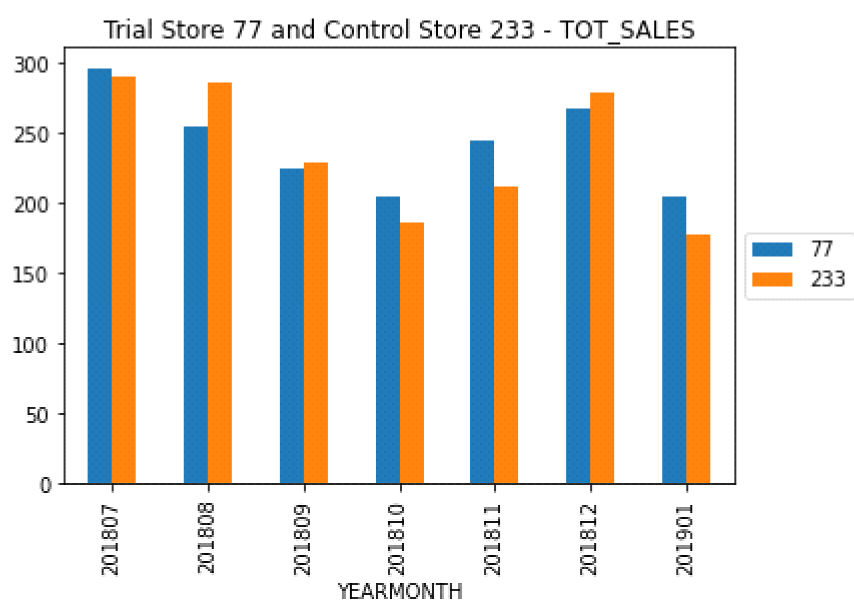
2.Trial store 86: Store 155

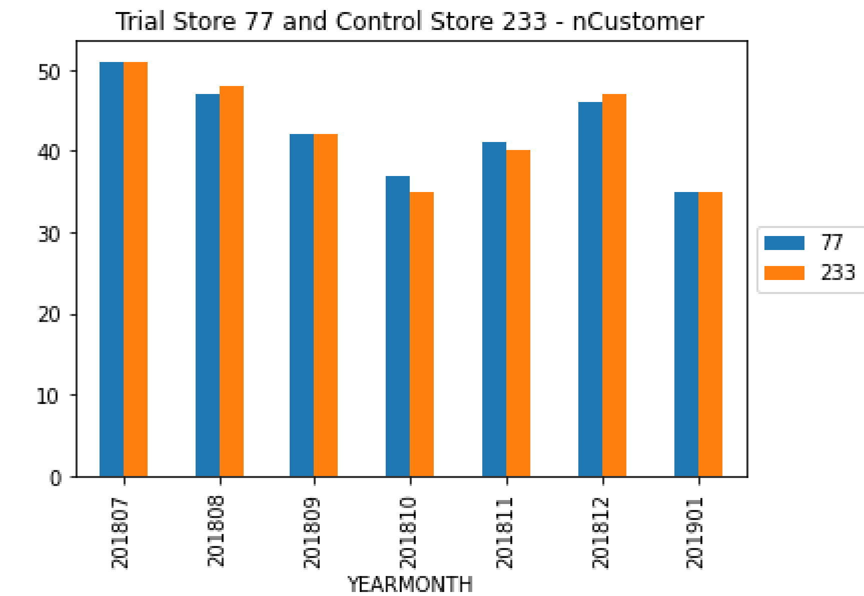
3.Trial store 88: Store 40

In [22] : trial_control_dic = {77:233, 86:155, 88:40}

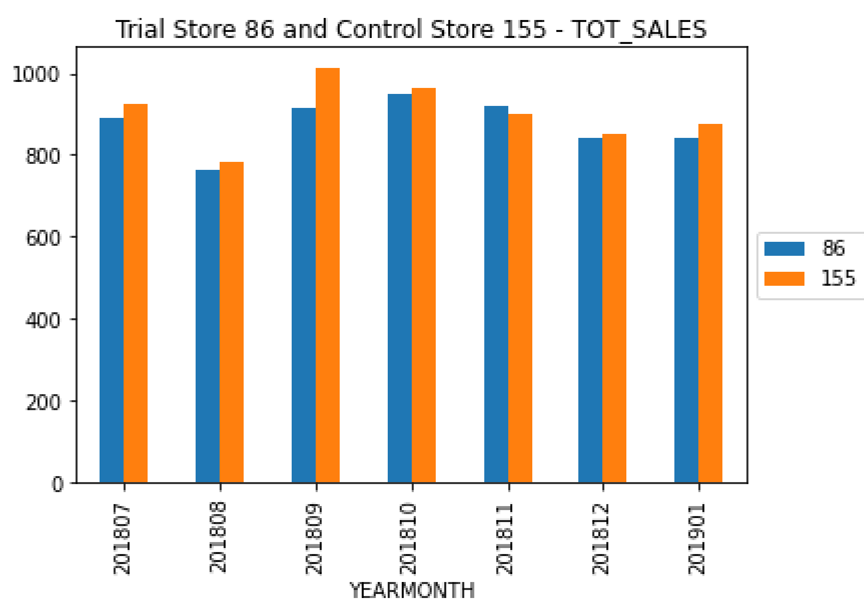
```
for key, val in trial_control_dic.items():

pretrial_full_observ[pretrial_full_observ["STORE_NBR"].isin([key, val])].groupby(
        ["YEARMONTH", "STORE_NBR"]).sum()["TOT_SALES"].unstack().plot.bar()
    plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
    plt.title("Trial Store "+str(key)+" and Control Store "+str(val)+" - TOT_SALES")
    plt.show()
```

```
pretrial_full_observ[pretrial_full_observ["STORE_NBR"].isin([
key, val])].groupby(
    ["YEARMONTH",
"STORE_NBR"]).sum()["nCustomers"].unstack().plot.bar()
    plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
    plt.title("Trial Store "+str(key)+" and Control Store
"+str(val)+" - nCustomer")
    plt.show()
    print("\n")
```

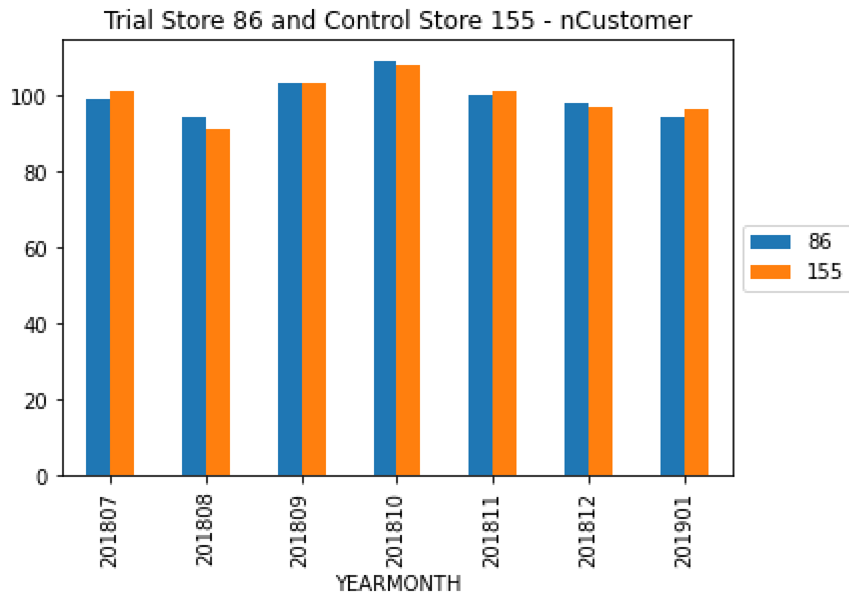




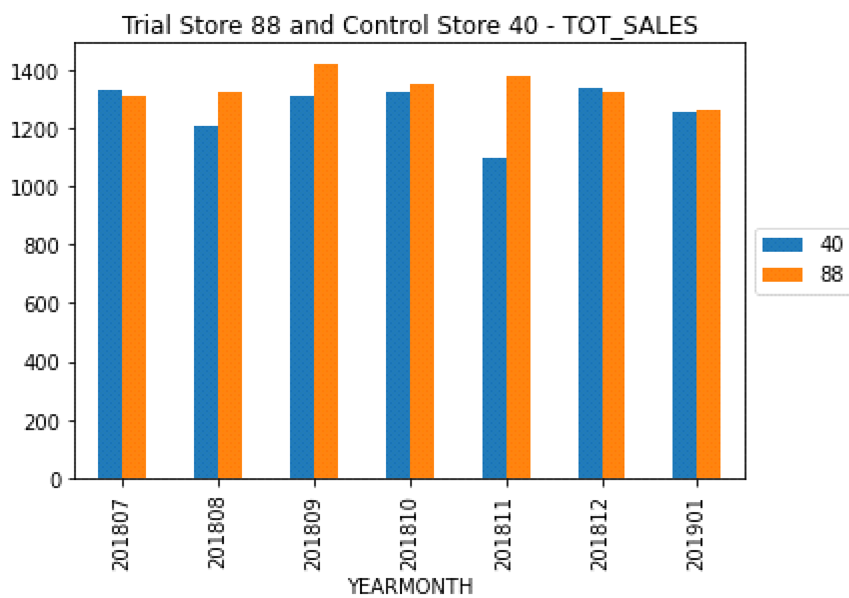
Trial Store 77 and Control Store 233 - nCustomer
0
10
20
30
40
50
77
233
201807
201808
201809
201810
201811
201812
201901
YEARMONTH



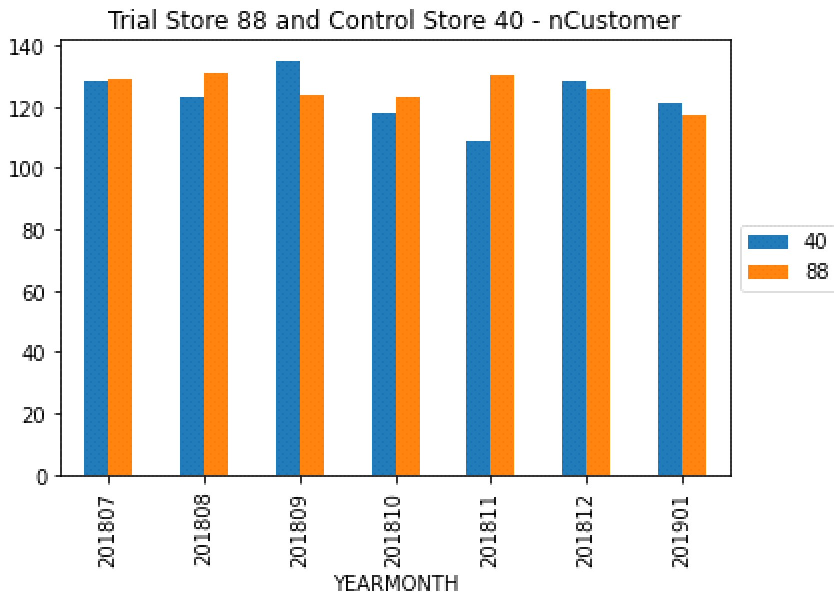
Trial Store 86 and Control Store 155 - TOT_SALES
0
200
400
600
800
1000
86
155
201807
201808
201809
201810
201811
201812
201901
YEARMONTH



Trial Store 86 and Control Store 155 - nCustomer
100
80
60
40
20
0
201807
201808
201809
201810
201811
201812
201901
YEARMONTH
86
155



Trial Store 88 and Control Store 40 - TOT_SALES
1400
1200
1000
800
600
400
200
0
201807
201808
201809
201810
201811
201812
201901
YEARMONTH
40
88



Next we'll compare the performance of Trial stores to Control stores during the trial period. To ensure their performance is comparable during Trial period, we need to scale (multiply to ratio of trial / control) all of Control stores' performance to Trial store's performance during pre-trial. Starting with TOT_SALES.

In [23] : #Ratio of Store 77 and its Control store.

sales_ratio_77 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 77]["TOT_SALES"].sum() / pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 233]["TOT_SALES"].sum()

#Ratio of Store 86 and its Control store.

sales_ratio_86 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 86]["TOT_SALES"].sum() /

pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 155]["TOT_SALES"].sum()

#Ratio of Store 77 and its Control store.

sales_ratio_88 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 88]["TOT_SALES"].sum() / pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 40]["TOT_SALES"].sum()

In [24] : trial_full_observ = full_observ[(full_observ["YEARMONTH"] >= 201902) & (full_observ["YEARMONTH"] <= 201904)]

scaled_sales_control_stores = full_observ[full_observ["STORE_NBR"].isin([233, 155, 40])][["STORE_NBR", "YEARMONTH", "TOT_SALES"]]

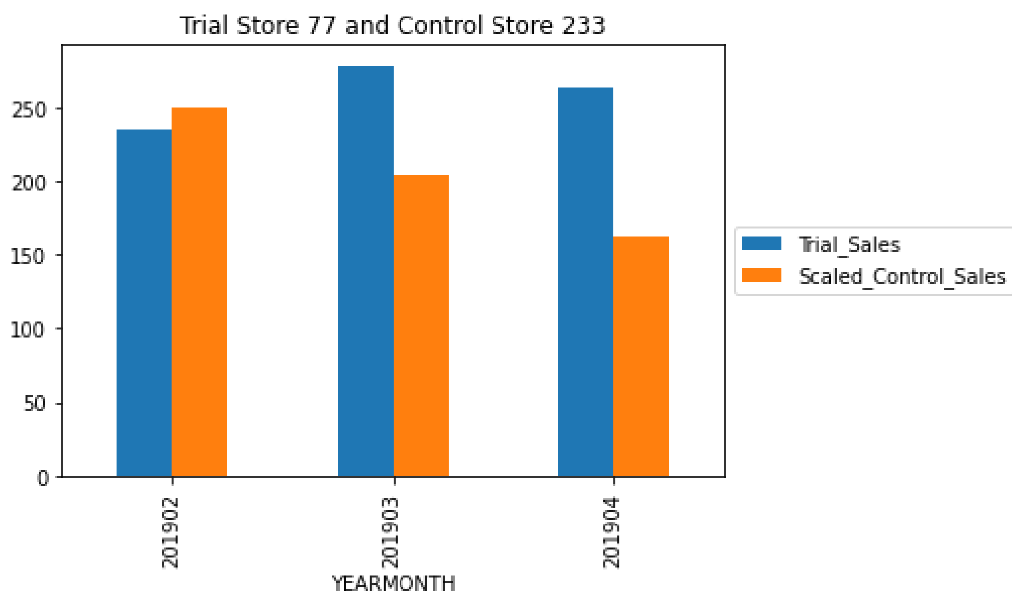
```
def scaler(row):
    if row["STORE_NBR"] == 233:
        return row["TOT_SALES"] * sales_ratio_77
    elif row["STORE_NBR"] == 155:
        return row["TOT_SALES"] * sales_ratio_86
    elif row["STORE_NBR"] == 40:
        return row["TOT_SALES"] * sales_ratio_88
```

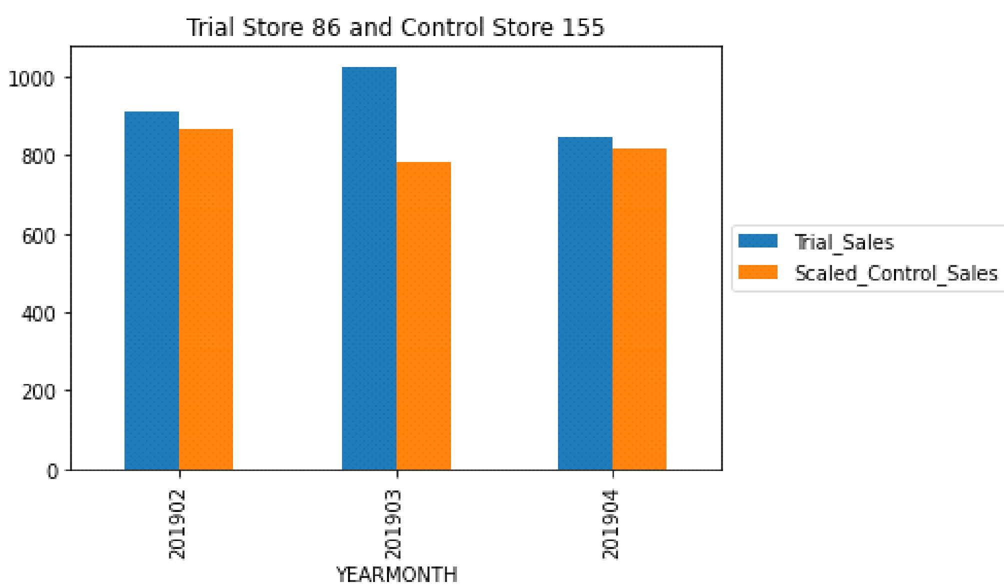
scaled_sales_control_stores["ScaledSales"] =

```
scaled_sales_control_stores.apply(lambda row: scaler(row), axis=1)

trial_scaled_sales_control_stores = scaled_sales_control_stores[(scaled_sales_control_stores["YEARMONTH"] >= 201902) & (scaled_sales_control_stores["YEARMONTH"] <= 201904)]
pretrial_scaled_sales_control_stores = scaled_sales_control_stores[scaled_sales_control_stores["YEARMONTH"] < 201902]

percentage_diff = {}

for trial, control in trial_control_dic.items():
    a = trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["STORE_NBR"] == control]
    b = trial_full_observ[trial_full_observ["STORE_NBR"] == trial][["STORE_NBR", "YEARMONTH", "TOT_SALES"]]
    percentage_diff[trial] = b["TOT_SALES"].sum() / a["ScaledSales"].sum()
    b[["YEARMONTH", "TOT_SALES"]].merge(a[["YEARMONTH", "ScaledSales"]],on="YEARMONTH").set_index("YEARMONTH").rename(columns={"ScaledSales":"Scaled_Control_Sales", "TOT_SALES":"Trial_Sales"}).plot.bar()
```

plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))

plt.title("Trial Store "+str(trial)+" and Control Store "+str(control))





In [26] : percentage_diff

OUT [26] : {77: 1.2615468650086274, 86: 1.13150143573637, 88: 1.0434583458542188}

In [27] : temp1 = scaled_sales_control_stores.sort_values(by=["STORE_NBR", "YEARMONTH"], ascending=[False, True]).reset_index().drop(["TOT_SALES", "index"], axis=1)

temp2 = full_observ[full_observ["STORE_NBR"].isin([77,86,88])][["STORE_NBR", "YEARMONTH", "TOT_SALES"]].reset_index().drop(["index", "YEARMONTH"], axis=1)

scaledsales_vs_trial = pd.concat([temp1, temp2], axis=1)

scaledsales_vs_trial.columns = ["c_STORE_NBR", "YEARMONTH", "c_ScaledSales", "t_STORE_NBR", "t_TOT_SALES"]

```
scaledsales_vs_trial["Sales_Percentage_Diff"] = (scaledsales_vs_trial["t_TOT_SALES"] - scaledsales_vs_trial["c_ScaledSales"]) / (((scaledsales_vs_trial["t_TOT_SALES"] + scaledsales_vs_trial["c_ScaledSales"])/2))

def label_period(cell):
    if cell < 201902:
        return "pre"
    elif cell > 201904:
        return "post"
    else:
        return "trial"

scaledsales_vs_trial["trial_period"] = scaledsales_vs_trial["YEARMONTH"].apply(lambda cell: label_period(cell))

scaledsales_vs_trial[scaledsales_vs_trial["trial_period"] == "trial"]
```

Out[27]:

	c_STORE_NBR	YEARMONTH	c_ScaledSales	t_STORE_NBR	t_TOT_SALES	Sales_Percentage_Diff	trial_period
7	233	201902	249.762622	77	235.0	-0.060907	trial
8	233	201903	203.802205	77	278.5	0.309755	trial
9	233	201904	162.345704	77	263.5	0.475075	trial
19	155	201902	864.522060	86	913.2	0.054764	trial
20	155	201903	780.320405	86	1026.8	0.272787	trial
21	155	201904	819.317024	86	848.2	0.034642	trial
31	40	201902	1434.399269	88	1370.2	-0.045781	trial
32	40	201903	1352.064709	88	1477.2	0.088458	trial
33	40	201904	1321.797762	88	1439.4	0.085182	trial

Check significance of Trial minus Control stores TOT_SALES

Percentage Difference Pre-Trial vs Trial.

Step 1: Check null hypothesis of 0 difference between control store's Pre-Trial and Trial period performance.

Step 2: Proof control and trial stores are similar statistically

Check p-value of control store's Pre-Trial vs Trial store's Pre-Trial. If <5%, it is significantly different. If >5%, it is not significantly different (similar).

Step 3: After checking Null Hypothesis of first 2 step to be true, we can check Null Hypothesis of Percentage Difference between Trial and Control stores during pre-trial is the same as during trial.

Check T-Value of Percentage Difference of each Trial month (Feb, March, April 2019). Mean is mean of Percentage Difference during pre-trial. Standard deviation is stdev of Percentage Difference during pre-trial. Formula is Trial month's Percentage Difference minus Mean, divided by Standard deviation. Compare each T-Value with 95% percentage significance critical t-value of 6 degrees of freedom (7 months of sample - 1)

In [28] : from scipy.stats import ttest_ind, t

```
# Step 1
for num in [40, 155, 233]:
    print("Store", num)

print(ttest_ind(pretrial_scaled_sales_control_stores[pretrial_scal
ed_sales_control_stores["STORE_NBR"] ==
num]["ScaledSales"],

trial_scaled_sales_control_stores[trial_scaled_sales_control_stor
es["STORE_NBR"] == num]["ScaledSales"],
                    equal_var=False), '\n')

#print(len(pretrial_scaled_sales_control_stores[pretrial_scaled_s
ales_control_stores["STORE_NBR"] == num]["ScaledSales"]),
len(trial_scaled_sales_control_stores[trial_scaled_sales_control_
stores["STORE_NBR"] == num]["ScaledSales"]))

alpha = 0.05
print("Critical t-value for 95% confidence interval:")
print(t.ppf((alpha/2, 1-alpha/2),
df=min([len(pretrial_scaled_sales_control_stores[pretrial_scaled
_sales_control_stores["STORE_NBR"] == num]),

len(trial_scaled_sales_control_stores[trial_scaled_sales_control_
stores["STORE_NBR"] == num])])-1))
```

Store 40

Ttest_indResult(statistic=-0.5958372343168585, pvalue=0.5722861621434009)

Store 155

Ttest_indResult(statistic=1.429195687929098, pvalue=0.19727058651603258)

Store 233

Ttest_indResult(statistic=1.1911026010974504, pvalue=0.29445006064862156)

Critical t-value for 95% confidence interval:

[-4.30265273 4.30265273]

In [29] : a = pretrial_scaled_sales_control_stores[pretrial_scaled_sales_control_stores["STORE_NBR"] == 40]["ScaledSales"]

b = trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["STORE_NBR"] == 40]["ScaledSales"]

Null hypothesis is true. There isn't any statistically significant difference between control store's scaled Pre-Trial and Trial period sales.

In [30] : # Step 2

```
for trial, cont in trial_control_dic.items():
    print("Trial store:", trial, ", Control store:", cont)

print(ttest_ind(pretrial_full_observ[pretrial_full_observ["STOR
E_NBR"] == trial]["TOT_SALES"],

pretrial_scaled_sales_control_stores[pretrial_scaled_sales_contr
ol_stores["STORE_NBR"] == cont]["ScaledSales"],
                    equal_var=True), '\n')

#print(len(pretrial_full_observ[pretrial_full_observ["STORE_N
BR"] ==
trial]["TOT_SALES"]),len(pretrial_scaled_sales_control_stores[
pretrial_scaled_sales_control_stores["STORE_NBR"] ==
cont]["ScaledSales"]))

alpha = 0.05
print("Critical t-value for 95% confidence interval:")
print(t.ppf((alpha/2, 1-alpha/2),
df=len(pretrial_full_observ[pretrial_full_observ["STORE_NBR
"] == trial])-1))
```

Trial store: 77 , Control store: 233

Ttest_indResult(statistic=-1.2533353315065926e-15,
pvalue=0.9999999999999999)

Trial store: 86 , Control store: 155

Ttest_indResult(statistic=0.0, pvalue=1.0)

Trial store: 88 , Control store: 40

Ttest_indResult(statistic=0.0, pvalue=1.0)

Critical t-value for 95% confidence interval:

[-2.44691185 2.44691185]

Null hypothesis is true. There isn't any statistically significant difference between Trial store's sales and Control store's scaled-sales performance during pre-trial.

In [31] : # Step 3

```
for trial, cont in trial_control_dic.items():
    print("Trial store:", trial, ", Control store:", cont)
    temp_pre =
scaledsales_vs_trial[(scaledsales_vs_trial["c_STORE_NBR"]
== cont) & (scaledsales_vs_trial["trial_period"]=="pre")]
    std = temp_pre["Sales_Percentage_Diff"].std()
    mean = temp_pre["Sales_Percentage_Diff"].mean()
    #print(std, mean)
    for t_month in
scaledsales_vs_trial[scaledsales_vs_trial["trial_period"] ==
```

```
"trial"]["YEARMONTH"].unique():
        pdif =
scaledsales_vs_trial[(scaledsales_vs_trial["YEARMONTH"] ==
t_month) & (scaledsales_vs_trial["t_STORE_NBR"] ==
trial)]["Sales_Percentage_Diff"]
        print(t_month,":",(float(pdif)-mean)/std)
    print('\n')

print("Critical t-value for 95% confidence interval:")
conf_intv_95 = t.ppf(0.95, df=len(temp_pre)-1)
print(conf_intv_95)
```

```
Trial store: 77 , Control store: 233
201902 : -0.7171038288055888
201903 : 3.035317928855662
201904 : 4.708944418758203


Trial store: 86 , Control store: 155
201902 : 1.4133618775921797
201903 : 7.123063846042149
201904 : 0.8863824572944162
```

Trial store: 88 , Control store: 40

201902 : -0.5481633746817604

201903 : 1.0089992743637755

201904 : 0.9710006270463645

Critical t-value for 95% confidence interval:

1.9431802803927816

There are 3 months' increase in performance that are statistically significant (Above the 95% confidence interval t-score):

March and April trial months for trial store 77

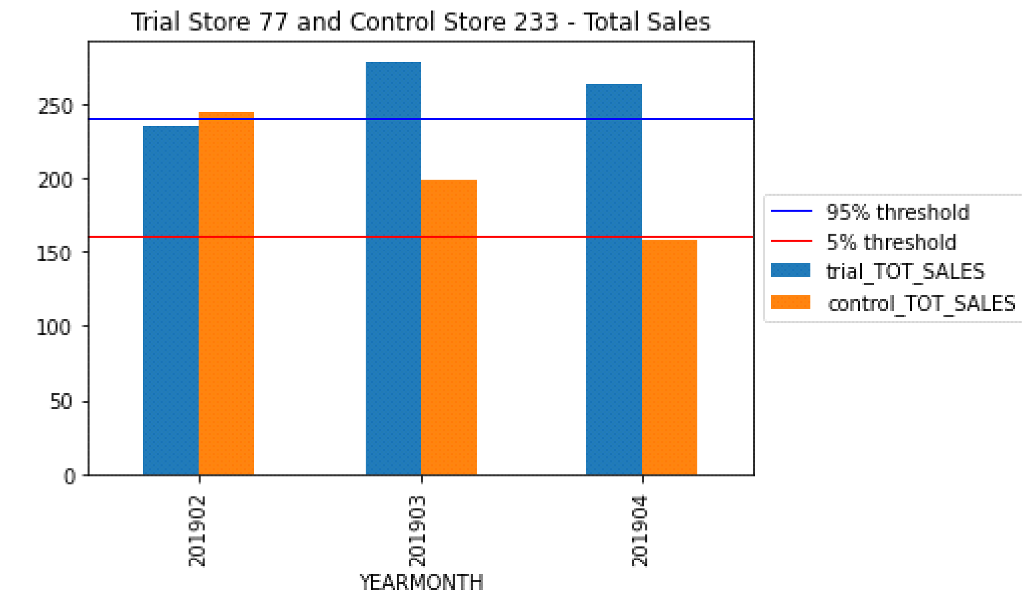
March trial months for trial store 86

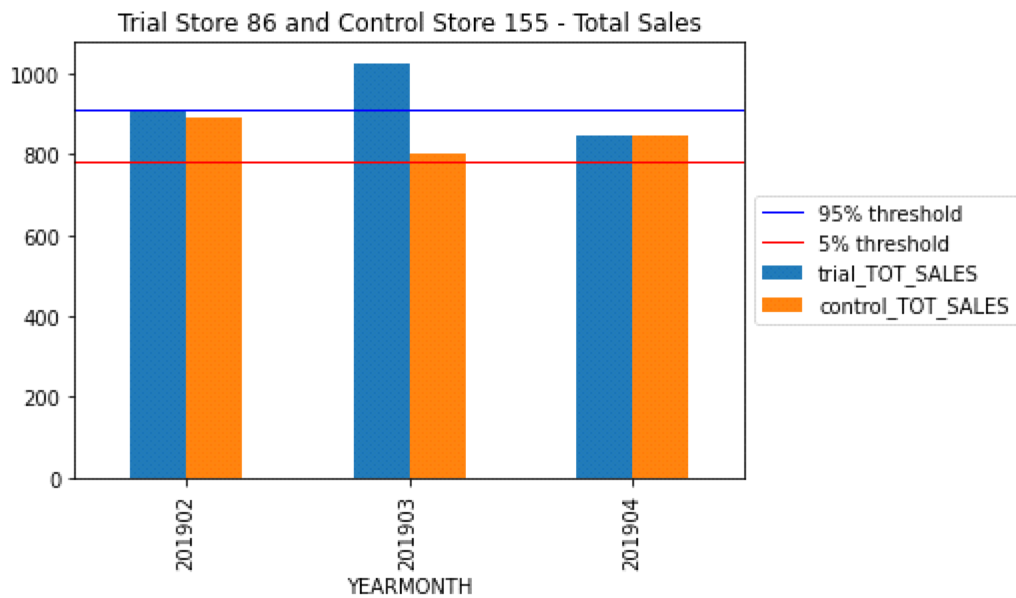
In [32] : for trial, control in trial_control_dic.items():

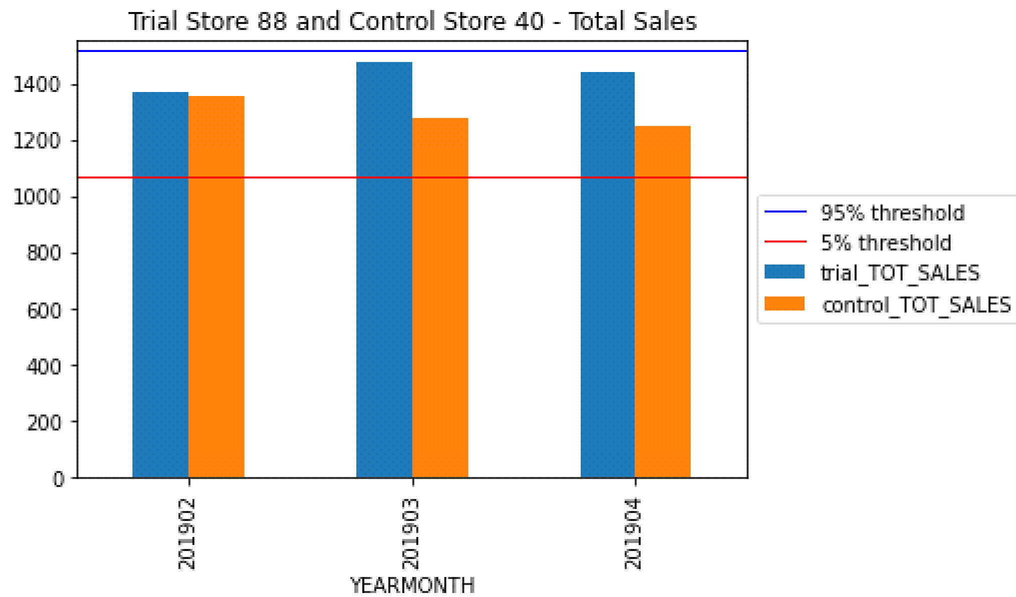
```
    a = trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["STORE_NBR"] == control].rename(columns={"TOT_SALES": "control_TOT_SALES"})
    b = trial_full_observ[trial_full_observ["STORE_NBR"] == trial][["STORE_NBR", "YEARMONTH",
```

```
"TOT_SALES"]].rename(columns={"TOT_SALES": "trial_TOT_SALES"})

    comb = b[["YEARMONTH", "trial_TOT_SALES"]].merge(a[["YEARMONTH", "control_TOT_SALES"]],on="YEARMONTH").set_index("YEARMONTH")

    comb.plot.bar()

    cont_sc_sales = trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["STORE_NBR"] == control]["TOT_SALES"]

    std = scaledsales_vs_trial[(scaledsales_vs_trial["c_STORE_NBR"] == control) & (scaledsales_vs_trial["trial_period"]=="pre")]["Sales_Percentage_Diff"].std()

    thresh95 = cont_sc_sales.mean() + (cont_sc_sales.mean() * std * 2)

    thresh5 = cont_sc_sales.mean() - (cont_sc_sales.mean() * std * 2)

    plt.axhline(y=thresh95,linewidth=1, color='b', label="95% threshold")

    plt.axhline(y=thresh5,linewidth=1, color='r', label="5% threshold")

    plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))

    plt.title("Trial Store "+str(trial)+" and Control Store "+str(control)+" - Total Sales")
```

```
plt.savefig("TS {} and CS {} - TOT_SALES.png".format(trial,control), bbox_inches="tight")
```







In [33] : #Ratio of Store 77 and its Control store.

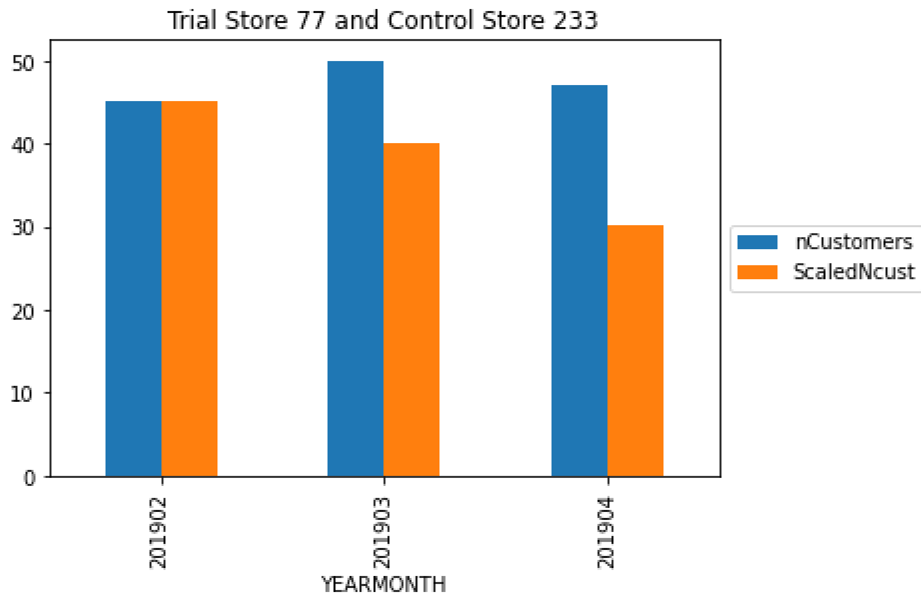
```
ncust_ratio_77 =
pretrial_full_observ[pretrial_full_observ["STORE_NBR"] ==
77]["nCustomers"].sum() /
pretrial_full_observ[pretrial_full_observ["STORE_NBR"] ==
233]["nCustomers"].sum()


#Ratio of Store 86 and its Control store.

ncust_ratio_86 =
pretrial_full_observ[pretrial_full_observ["STORE_NBR"] ==
86]["nCustomers"].sum() /
pretrial_full_observ[pretrial_full_observ["STORE_NBR"] ==
155]["nCustomers"].sum()


#Ratio of Store 77 and its Control store.

ncust_ratio_88 =
```

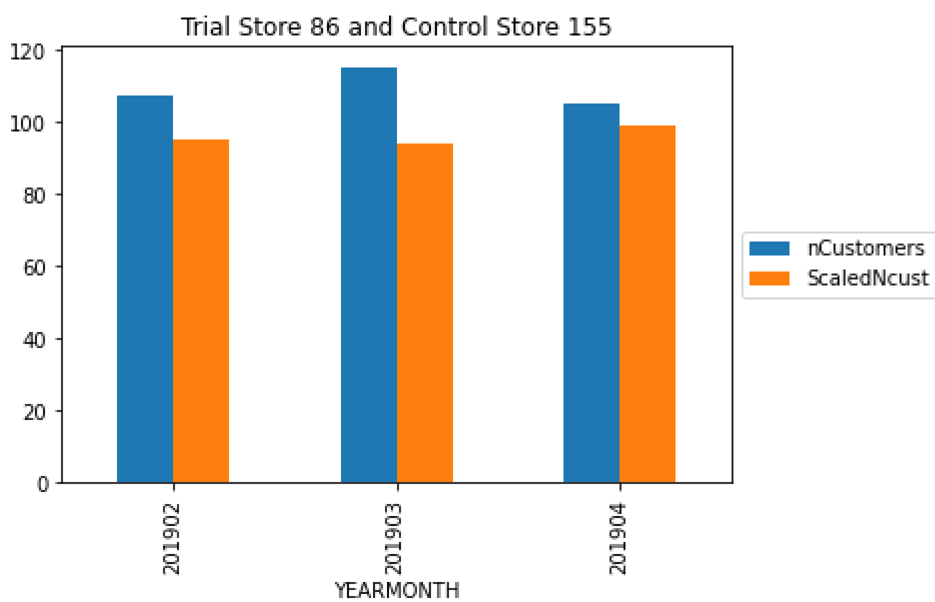
```
pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 88]["nCustomers"].sum() / pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 40]["nCustomers"].sum()
```

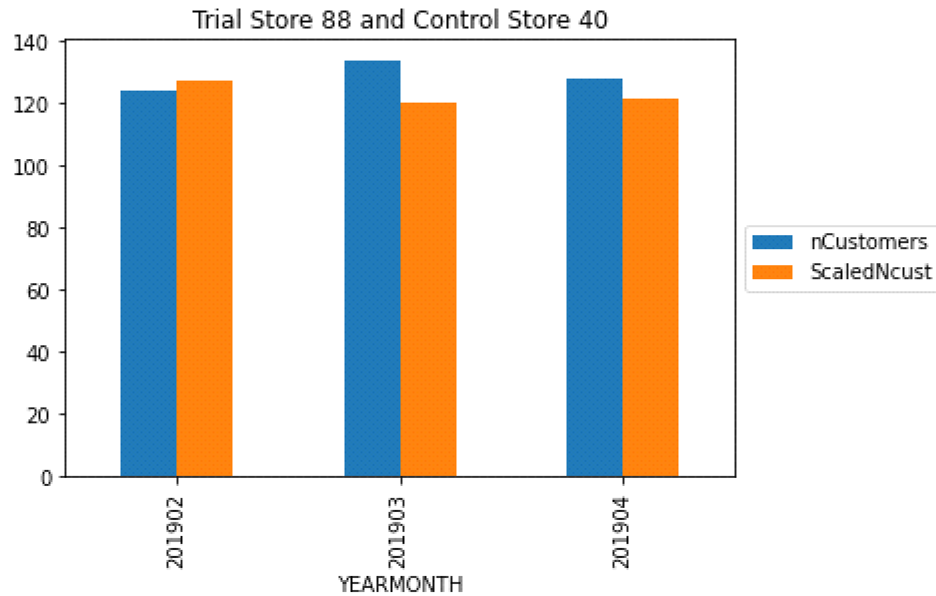
In [34] :

```
#trial_full_observ = full_observ[(full_observ["YEARMONTH"] >= 201902) & (full_observ["YEARMONTH"] <= 201904)]

scaled_ncust_control_stores = full_observ[full_observ["STORE_NBR"].isin([233, 155, 40])][["STORE_NBR", "YEARMONTH", "nCustomers"]]


def scaler_c(row):
    if row["STORE_NBR"] == 233:
        return row["nCustomers"] * ncust_ratio_77
    elif row["STORE_NBR"] == 155:
        return row["nCustomers"] * ncust_ratio_86
    elif row["STORE_NBR"] == 40:
        return row["nCustomers"] * ncust_ratio_88


scaled_ncust_control_stores["ScaledNcust"] = scaled_ncust_control_stores.apply(lambda row: scaler_c(row), axis=1)


trial_scaled_ncust_control_stores = scaled_ncust_control_stores[(scaled_ncust_control_stores["YE
```

```
ARMONTH"] >= 201902) &
(scaled_ncust_control_stores["YEARMONTH"] <= 201904)]
pretrial_scaled_ncust_control_stores =
scaled_ncust_control_stores[scaled_ncust_control_stores["YEA
RMONTH"] < 201902]


ncust_percentage_diff = {}


for trial, control in trial_control_dic.items():
    a =
trial_scaled_ncust_control_stores[trial_scaled_ncust_control_sto
res["STORE_NBR"] == control]
    b = trial_full_observ[trial_full_observ["STORE_NBR"] ==
trial][["STORE_NBR", "YEARMONTH", "nCustomers"]]
    ncust_percentage_diff[trial] = b["nCustomers"].sum() /
a["ScaledNcust"].sum()
    b[["YEARMONTH",
"nCustomers"]].merge(a[["YEARMONTH",
"ScaledNcust"]],on="YEARMONTH").set_index("YEARMON
TH").rename(columns={"ScaledSales":"Scaled_Control_nCust"
, "TOT_SALES":"Trial_nCust"}).plot.bar()
    plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
    plt.title("Trial Store "+str(trial)+" and Control Store
"+str(control))
```


Trial Store 77 and Control Store 233
50
40
30
20
10
0
nCustomers
ScaledNcust
201902
201903
201904
YEARMONTH


Trial Store 86 and Control Store 155
120
100
80
60
40
20
0
nCustomers
ScaledNcust
201902
201903
201904
YEARMONTH



In [35] : ncust_percentage_diff

OUT [35] : {77: 1.2306529009742622, 86: 1.1354166666666667, 88: 1.0444876946258161}

In [36] : temp1 = scaled_ncust_control_stores.sort_values(by=["STORE_NBR", "YEARMONTH"], ascending=[False, True]).reset_index().drop(["nCustomers", "index"], axis=1)

temp2 = full_observ[full_observ["STORE_NBR"].isin([77,86,88])][["STORE_NBR", "YEARMONTH", "nCustomers"]].reset_index().drop(["index", "YEARMONTH"], axis=1)

scaledncust_vs_trial = pd.concat([temp1, temp2], axis=1)

scaledncust_vs_trial.columns = ["c_STORE_NBR", "YEARMONTH", "c_ScaledNcust", "t_STORE_NBR", "t_nCustomers"] scaledncust_vs_trial["nCust_Percentage_Diff"] = (scaledncust_vs_trial["t_nCustomers"] - scaledncust_vs_trial["c_ScaledNcust"]) / (((scaledncust_vs_trial["t_nCustomers"] + scaledncust_vs_trial["c_ScaledNcust"])/2))

scaledncust_vs_trial["trial_period"] = scaledncust_vs_trial["YEARMONTH"].apply(lambda cell: label_period(cell))

scaledncust_vs_trial[scaledncust_vs_trial["trial_period"] == "trial"]

Out[36]:

	c_STORE_NBR	YEARMONTH	c_ScaledNcust	t_STORE_NBR	t_nCustomers	nCust_Percentage_Diff	trial_period
7	233	201902	45.151007	77	45	-0.003350	trial
8	233	201903	40.134228	77	50	0.218913	trial
9	233	201904	30.100671	77	47	0.438370	trial
19	155	201902	95.000000	86	107	0.118812	trial
20	155	201903	94.000000	86	115	0.200957	trial
21	155	201904	99.000000	86	105	0.058824	trial
31	40	201902	127.610209	88	124	-0.028697	trial
32	40	201903	120.464037	88	134	0.106388	trial
33	40	201904	121.484919	88	128	0.052228	trial

Check significance of Trial minus Control stores nCustomers Percentage Difference Pre-Trial vs Trial.

Step 1: Check null hypothesis of 0 difference between control store's Pre-Trial and Trial period performance.

Step 2: Proof control and trial stores are similar statistically

Step 3: After checking Null Hypothesis of first 2 step to be true, we can check Null Hypothesis of Percentage Difference between Trial and Control stores during pre-trial is the same as during trial.

In [37] : # Step 1

```
for num in [40, 155, 233]:
    print("Store", num)

print(ttest_ind(pretrial_scaled_ncust_control_stores[pretrial_scaled_ncust_control_stores["STORE_NBR"] == num]["ScaledNcust"],

trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["STORE_NBR"] == num]["ScaledNcust"],
                   equal_var=False), '\n')

alpha = 0.05
print("Critical t-value for 95% confidence interval:")
print(t.ppf((alpha/2, 1-alpha/2), df=min([len(pretrial_scaled_ncust_control_stores[pretrial_scaled_ncust_control_stores["STORE_NBR"] == num]),

len(trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["STORE_NBR"] == num])])-1))
```

Store 40

Ttest_indResult(statistic=0.644732693420032, pvalue=0.5376573016017127)

Store 155

Ttest_indResult(statistic=1.3888888888888882, pvalue=0.204345986327886)

Store 233

Ttest_indResult(statistic=0.8442563765225701, pvalue=0.4559280037660254)

Critical t-value for 95% confidence interval:

[-4.30265273 4.30265273]

In [38] : # Step 2

```
for trial, cont in trial_control_dic.items():
    print("Trial store:", trial, ", Control store:", cont)

print(ttest_ind(pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == trial]["nCustomers"],

pretrial_scaled_ncust_control_stores[pretrial_scaled_ncust_control_stores["STORE_NBR"] == cont]["ScaledNcust"],
                    equal_var=True), '\n')
```

alpha = 0.05

print("Critical t-value for 95% confidence interval:")

print(t.ppf((alpha/2, 1-alpha/2), df=len(pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == trial])-1))

Trial store: 77 , Control store: 233

Ttest_indResult(statistic=0.0, pvalue=1.0)

Trial store: 86 , Control store: 155

Ttest_indResult(statistic=0.0, pvalue=1.0)

Trial store: 88 , Control store: 40

Ttest_indResult(statistic=-7.648483953264653e-15, pvalue=0.9999999999999994)

Critical t-value for 95% confidence interval:

[-2.44691185 2.44691185]

In [39] : # Step 3

for trial, cont in trial_control_dic.items():

    print("Trial store:", trial, ", Control store:", cont)

    temp_pre =

```
scaledncust_vs_trial[(scaledncust_vs_trial["c_STORE_NBR"]
== cont) & (scaledncust_vs_trial["trial_period"]=="pre")]
    std = temp_pre["nCust_Percentage_Diff"].std()
    mean = temp_pre["nCust_Percentage_Diff"].mean()
    #print(std, mean)
    for t_month in
scaledncust_vs_trial[scaledncust_vs_trial["trial_period"] ==
"trial"]["YEARMONTH"].unique():
        pdif =
scaledncust_vs_trial[(scaledncust_vs_trial["YEARMONTH"]
== t_month) & (scaledncust_vs_trial["t_STORE_NBR"] ==
trial)]["nCust_Percentage_Diff"]
        print(t_month,":",(float(pdif)-mean)/std)
    print('\n')

print("Critical t-value for 95% confidence interval:")
conf_intv_95 = t.ppf(0.95, df=len(temp_pre)-1)
print(conf_intv_95)
```

Trial store: 77 , Control store: 233

201902 : -0.19886295797440687

201903 : 8.009609025380932

201904 : 16.114474772873923

Trial store: 86 , Control store: 155

201902 : 6.220524882227514

201903 : 10.52599074274189

201904 : 3.0763575852842706

Trial store: 88 , Control store: 40

201902 : -0.3592881735131531

201903 : 1.2575196020616801

201904 : 0.6092905590514273

Critical t-value for 95% confidence interval:

1.9431802803927816

There are 5 months' increase in performance that are statistically significant (Above the 95% confidence interval t-score):

March and April trial months for trial store 77

Feb, March and April trial months for trial store 86

In [40] : for trial, control in trial_control_dic.items():

```
    a = trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["STORE_NBR"] == control].rename(columns={"nCustomers": "control_nCustomers"})
    b = trial_full_observ[trial_full_observ["STORE_NBR"] == trial][["STORE_NBR", "YEARMONTH", "nCustomers"]].rename(columns={"nCustomers": "trial_nCustomers"})
    comb = b[["YEARMONTH", "trial_nCustomers"]].merge(a[["YEARMONTH", "control_nCustomers"]],on="YEARMONTH").set_index("YEARMONTH")
    comb.plot.bar()
    cont_sc_ncust = trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["STORE_NBR"] == control]["nCustomers"]
    std = scaledncust_vs_trial[(scaledncust_vs_trial["c_STORE_NBR"] == control) & (scaledncust_vs_trial["trial_period"]=="pre")]["nCust_Percentage_Diff"].std()
    thresh95 = cont_sc_ncust.mean() + (cont_sc_ncust.mean() * std * 2)
    thresh5 = cont_sc_ncust.mean() - (cont_sc_ncust.mean() * std * 2)
```

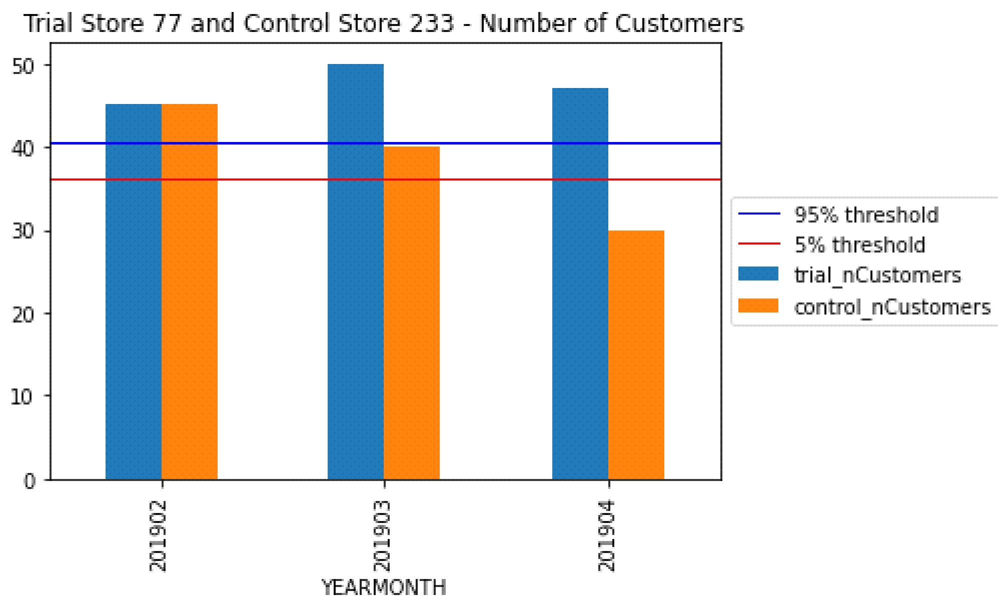
plt.axhline(y=thresh95,linewidth=1, color='b', label="95% threshold")

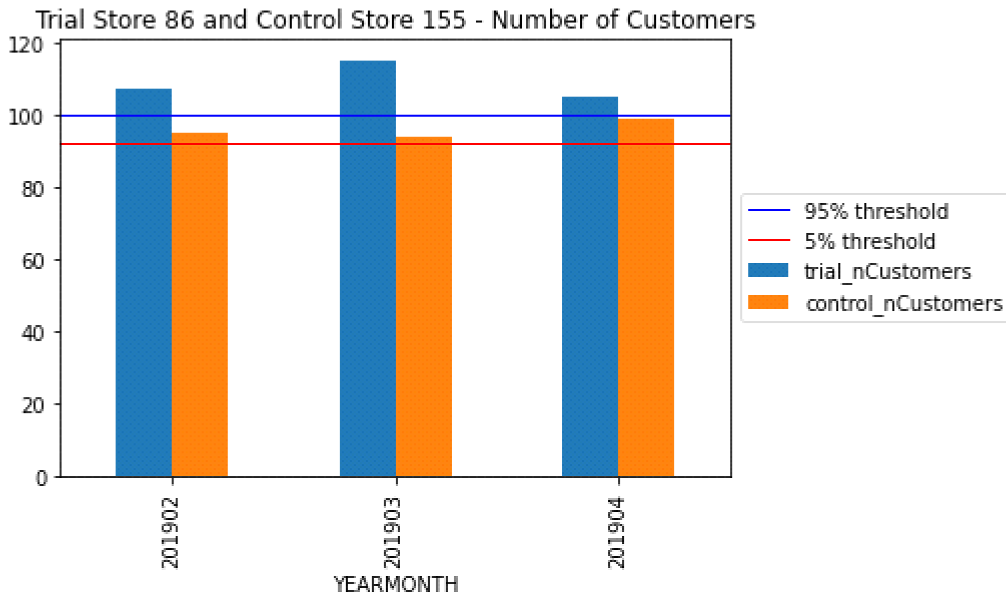
plt.axhline(y=thresh5,linewidth=1, color='r', label="5% threshold")

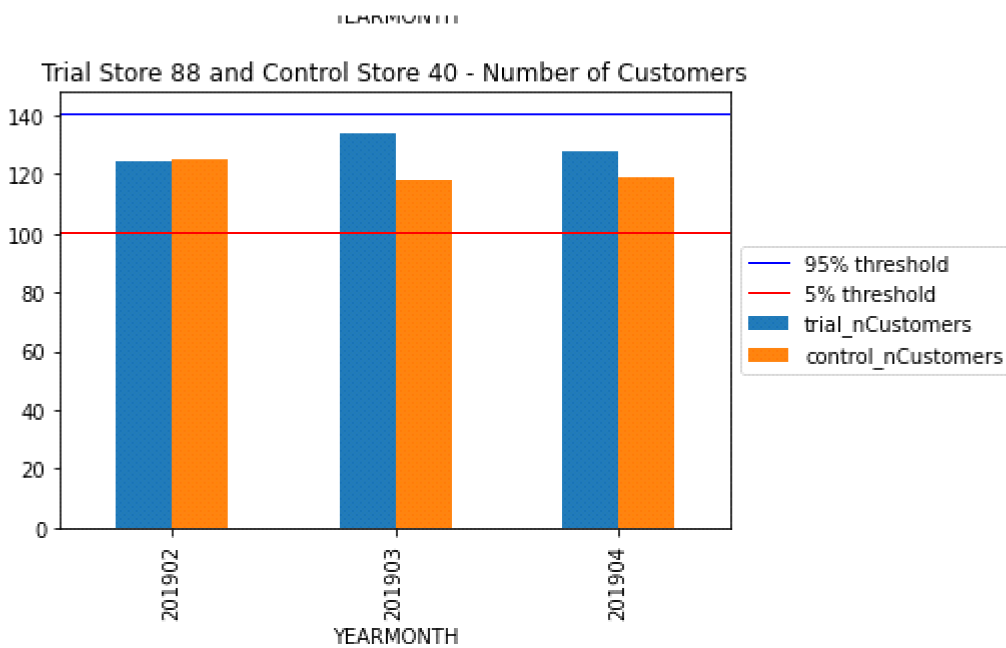
plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))

plt.title("Trial Store "+str(trial)+" and Control Store "+str(control)+" - Number of Customers")

plt.savefig("TS {} and CS {} - nCustomers.png".format(trial,control), bbox_inches="tight")







We can see that Trial store 77 sales for Feb, March, and April exceeds 95% threshold of control store. Same goes to store 86 sales for all 3 trial months.

1.Trial store 77: Control store 233

2.Trial store 86: Control store 155

3.Trial store 88: Control store 40

4.Both trial store 77 and 86 showed significant increase in Total Sales and Number of Customers during trial period. But not for trial store 88. Perhaps the client knows if there's anything about trial 88 that differs it from the other two trial.

5.Overall the trial showed positive significant result.