q-task-2

June 29, 2024

1 Experimentation and Uplift Testing

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

This can be broken by - 1. total sales revenue 2. total number of customers 3. 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 distannce eg 1 - (Observed distance - minimum distance)/(Minimum 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 customers or more purchases per customers per customers etc.

Main areas of Focus are -

1. Select control stores - Explore data, define metrics, visualize graphs.
2. Assessment of the trial - insights/ trends by comparing trial stores with control stores.
3. Collate findings - summarize and provide recommendations.

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
```

[2]:
```
qvi = pd.read_csv("/content/QVI_data.csv")
qvi.head()
```

[2]:

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE
0	1000	2018-10-17	1	1	5	Natural Chip Compny SeaSalt175g	2	6.0	175
1	1002	2018-09-16	1	2	58	Red Rock Deli Chikn&Garlic Aioli 150g	1	2.7	150
2	1003	2019-03-07	1	3	52				
3	1003	2019-03-08	1	4	106				
4	1004	2018-11-02	1	5	96				

```
2   Grain Waves Sour    Cream&Chives 210G         1        3.6        210
3  Natural ChipCo      Hony Soy Chckn175g         1        3.0        175
4           WW Original Stacked Chips 160g         1        1.9        160

        BRAND              LIFESTAGE PREMIUM_CUSTOMER
0     NATURAL  YOUNG SINGLES/COUPLES          Premium
1         RRD  YOUNG SINGLES/COUPLES       Mainstream
2     GRNWVES         YOUNG FAMILIES           Budget
3     NATURAL         YOUNG FAMILIES           Budget
4  WOOLWORTHS  OLDER SINGLES/COUPLES       Mainstream
```

[3]:
```
qvi.info()
```

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

[4]:
```
qvi["DATE"] = pd.to_datetime(qvi["DATE"])
qvi["YEARMONTH"] = qvi["DATE"].dt.strftime("%Y%m").astype("int")
```

Compile each stores monthly - 1. Total sales 2. Number of customers 3. Average transactions per customer 4. Average chips per customer 5. Average price per unit

[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
```

[6]:
```
qvi_monthly_metrics = monthly_store_metrics().reset_index()
qvi_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
```

[7]:
```
# Pre Trial Observation as this filter only stores with full 12 months␣
 ↪observation
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)
```

[7]:

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

	avgPricePerUnit
0	3.337097

```
1           3.261111
2           3.717333
3           3.243103
4           3.378947
5           3.326316
6           3.685714
12          3.278261
```

[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
```

[9]:
```
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)
```

[9]:

	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

[10]:
```
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
```

[11]:
```
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
```

[11]:

	TOT_SALES	nCustomers	nTxnPerCust	nChipsPerTxn	avgPricePerUnit	\
0	0.935431	0.980769	0.958035	0.739412	0.883569	
1	0.942972	0.951923	0.993823	0.802894	0.886328	
2	0.961503	0.836538	0.992126	0.730041	0.703027	
3	0.988221	0.932692	0.989514	0.940460	0.590528	
4	0.962149	0.951923	0.874566	0.730358	0.832481	
..	…	…	…	…	…	
2	0.207554	0.286822	0.462846	0.779879	0.923887	
3	0.346797	0.387597	0.571497	0.796875	0.971133	
4	0.286706	0.310078	0.623883	0.813241	0.966999	
5	0.347151	0.387597	0.376456	0.699748	0.962198	
6	0.402353	0.449612	0.450378	0.739714	0.971335	

	YEARMONTH	Trial_Str	Ctrl_Str	magnitude
0	201807	77	1	0.899443

```
1      201808          77          1    0.915588
2      201809          77          1    0.844647
3      201810          77          1    0.888283
4      201811          77          1    0.870296
..        …          …         …          …
2      201809          88        272    0.532198
3      201810          88        272    0.614780
4      201811          88        272    0.600181
5      201812          88        272    0.554630
6      201901          88        272    0.602678

[5397 rows x 9 columns]
```

We will 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.

[12]:
```
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
```

[13]:
```
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)])
```

[14]:
```
corr_weight = 0.5
dist_weight = 1 - corr_weight
```

[15]:
```
# Determining the top five highest composite score for each trial based on␣
 ↪Total sales
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      YEARMONTH  Corr_Score  magnitude  CompScore
218         77       233  201822.571429         1.0   0.986477   0.993238
239         77       255  201822.571429         1.0   0.979479   0.989739
177         77       188  201822.571429         1.0   0.977663   0.988831
```

```
49          77         53  201822.571429         1.0   0.976678   0.988339
120         77        131  201822.571429         1.0   0.976267   0.988134

     Trial_Str  Ctrl_Str      YEARMONTH  Corr_Score  magnitude  CompScore
356         86       109  201822.571429         1.0   0.966783   0.983391
401         86       155  201822.571429         1.0   0.965876   0.982938
464         86       222  201822.571429         1.0   0.962280   0.981140
467         86       225  201822.571429         1.0   0.960512   0.980256
471         86       229  201822.571429         1.0   0.951704   0.975852

     Trial_Str  Ctrl_Str      YEARMONTH  Corr_Score  magnitude  CompScore
551         88        40  201822.571429         1.0   0.941165   0.970582
538         88        26  201822.571429         1.0   0.904377   0.952189
582         88        72  201822.571429         1.0   0.903800   0.951900
517         88         4  201822.571429         1.0   0.903466   0.951733
568         88        58  201822.571429         1.0   0.891678   0.945839
```

[16]:
```
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)])
```

[17]:
```
# Determining the top five highest composite score for each trial based on no.
 ↪of customers

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')
```

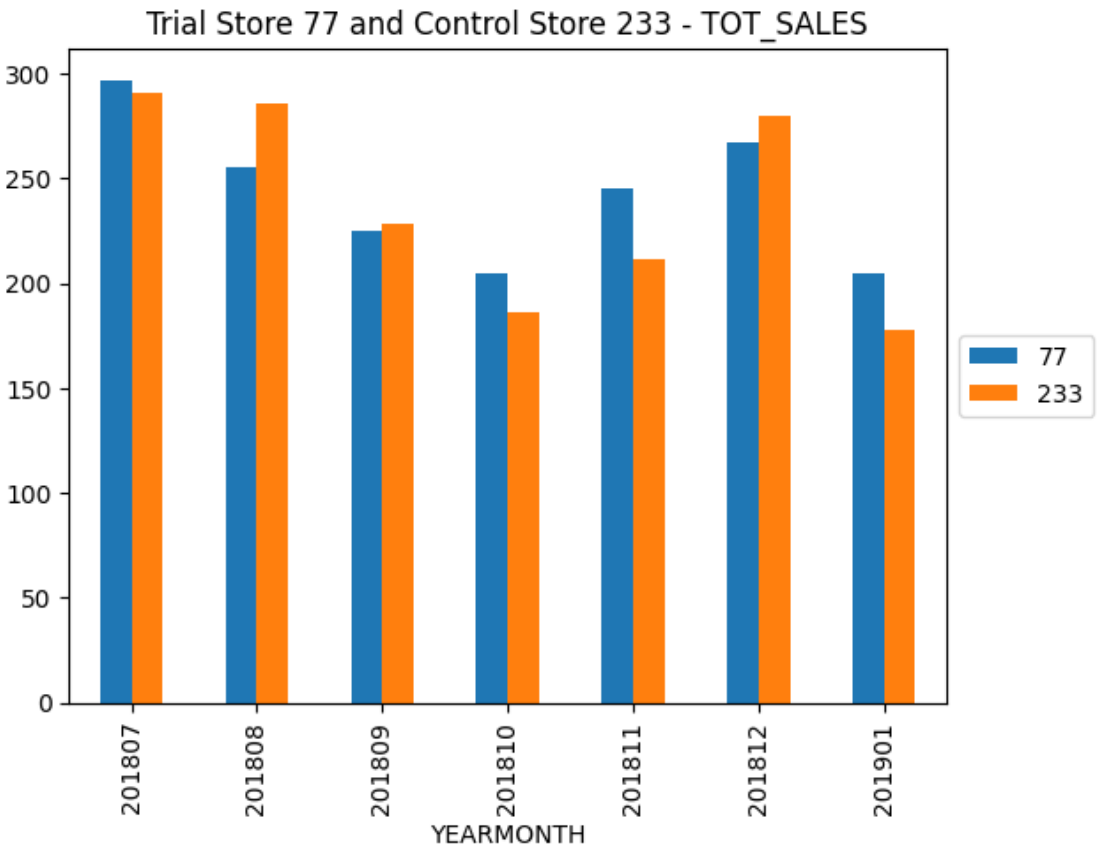
```
     Trial_Str  Ctrl_Str      YEARMONTH  Corr_Score  magnitude  CompScore
218         77       233  201822.571429         1.0   0.993132   0.996566
38          77        41  201822.571429         1.0   0.976648   0.988324
101         77       111  201822.571429         1.0   0.968407   0.984203
105         77       115  201822.571429         1.0   0.967033   0.983516
15          77        17  201822.571429         1.0   0.965659   0.982830

     Trial_Str  Ctrl_Str      YEARMONTH  Corr_Score  magnitude  CompScore
401         86       155  201822.571429         1.0   0.986772   0.993386
467         86       225  201822.571429         1.0   0.969577   0.984788
356         86       109  201822.571429         1.0   0.969577   0.984788
471         86       229  201822.571429         1.0   0.964286   0.982143
```

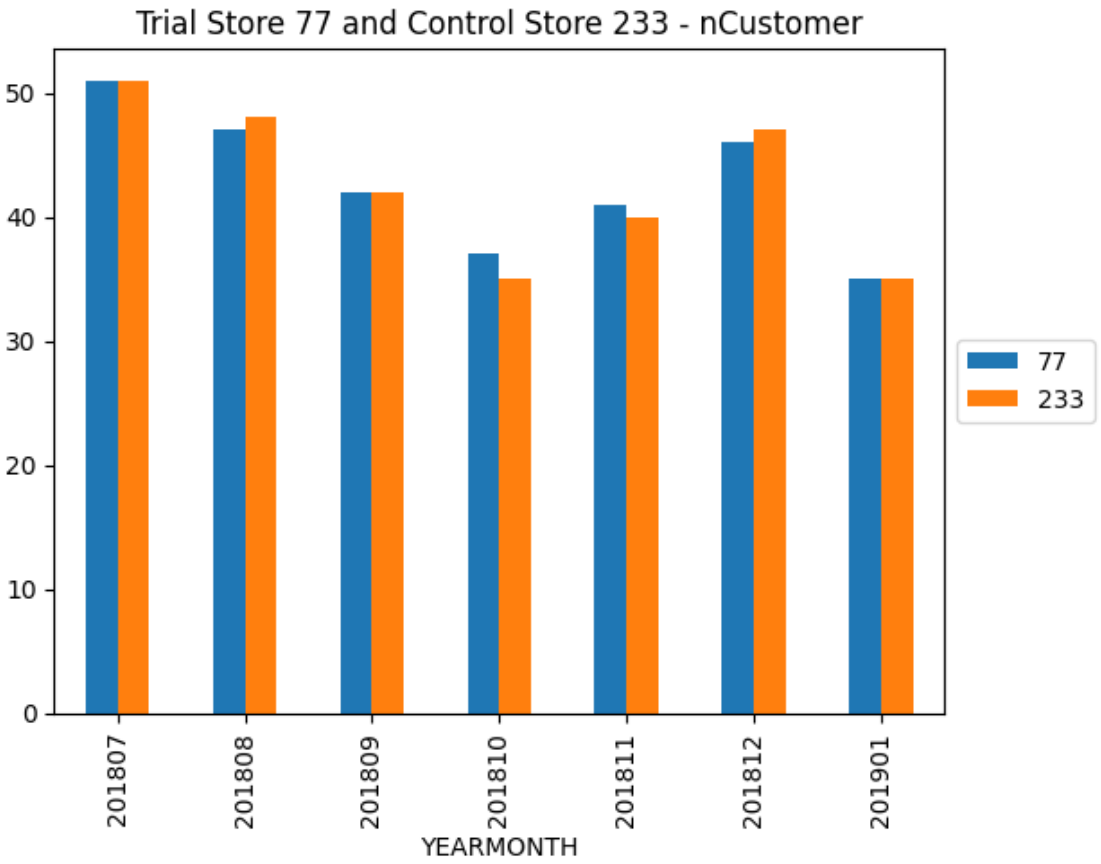
```
293          86         39  201822.571429          1.0    0.961640    0.980820

     Trial_Str  Ctrl_Str      YEARMONTH  Corr_Score  magnitude  CompScore
736         88       237  201822.571429         1.0   0.987818   0.993909
705         88       203  201822.571429         1.0   0.944629   0.972315
551         88        40  201822.571429         1.0   0.942414   0.971207
668         88       165  201822.571429         1.0   0.935770   0.967885
701         88       199  201822.571429         1.0   0.932447   0.966224
```

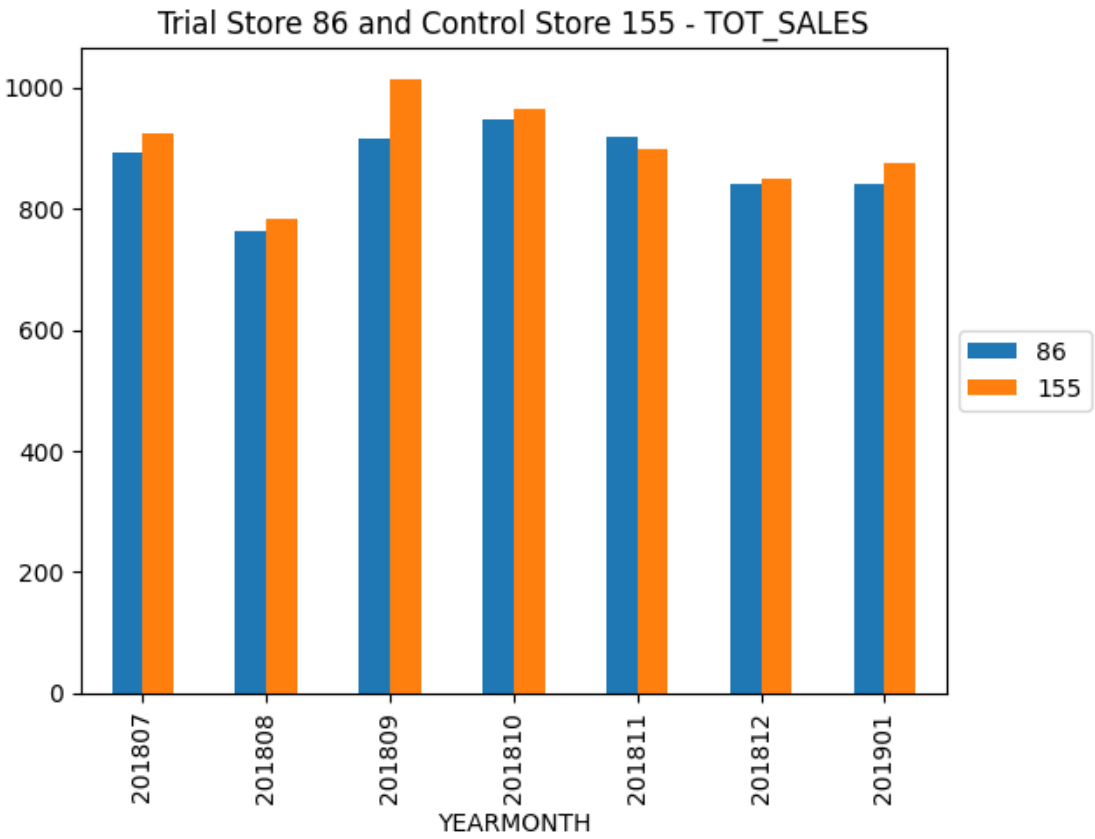
Similarities based on total sales : 1. Trial store 77: Store 233, 255, 188 2. Trial store 86: Store 109, 155, 222 3. Trial store 88: Store 40, 26, 72

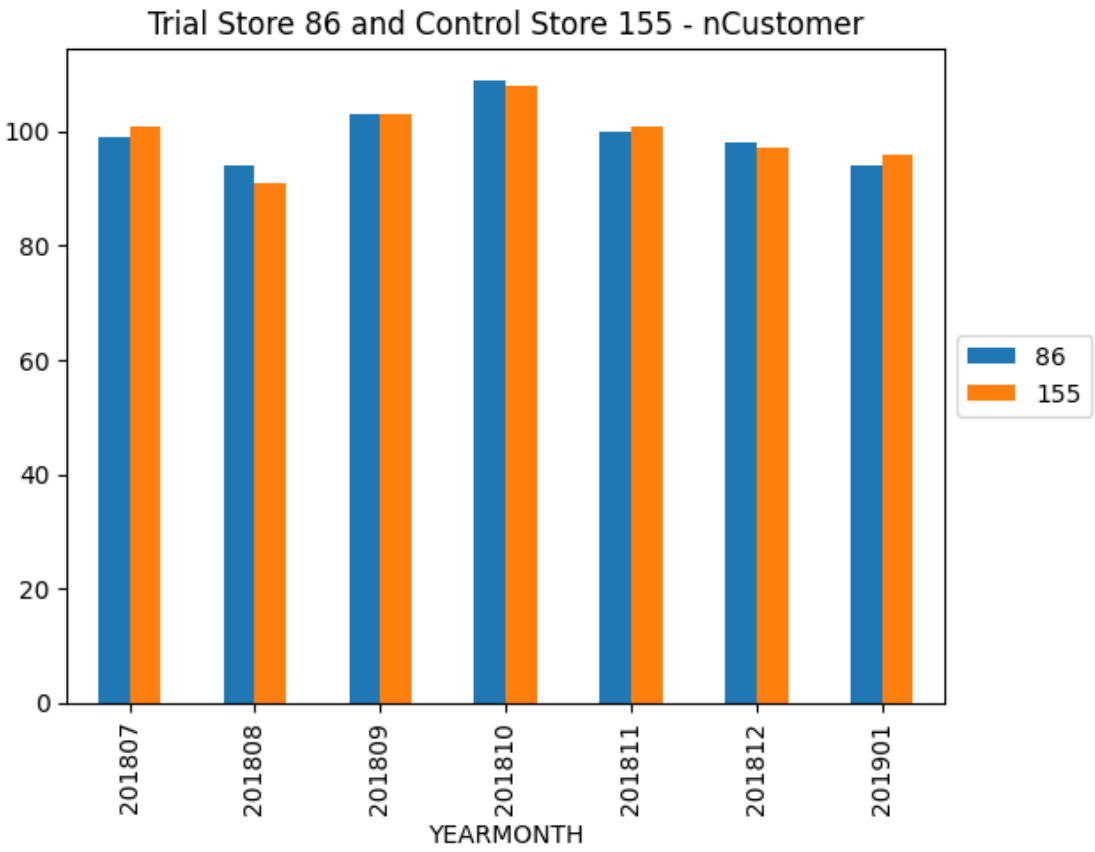
Similarities based on No.of Customers: 1. Trial store 77: Store 233 2. Trial store 86: Store 155 3. Trial store 88: Store 40

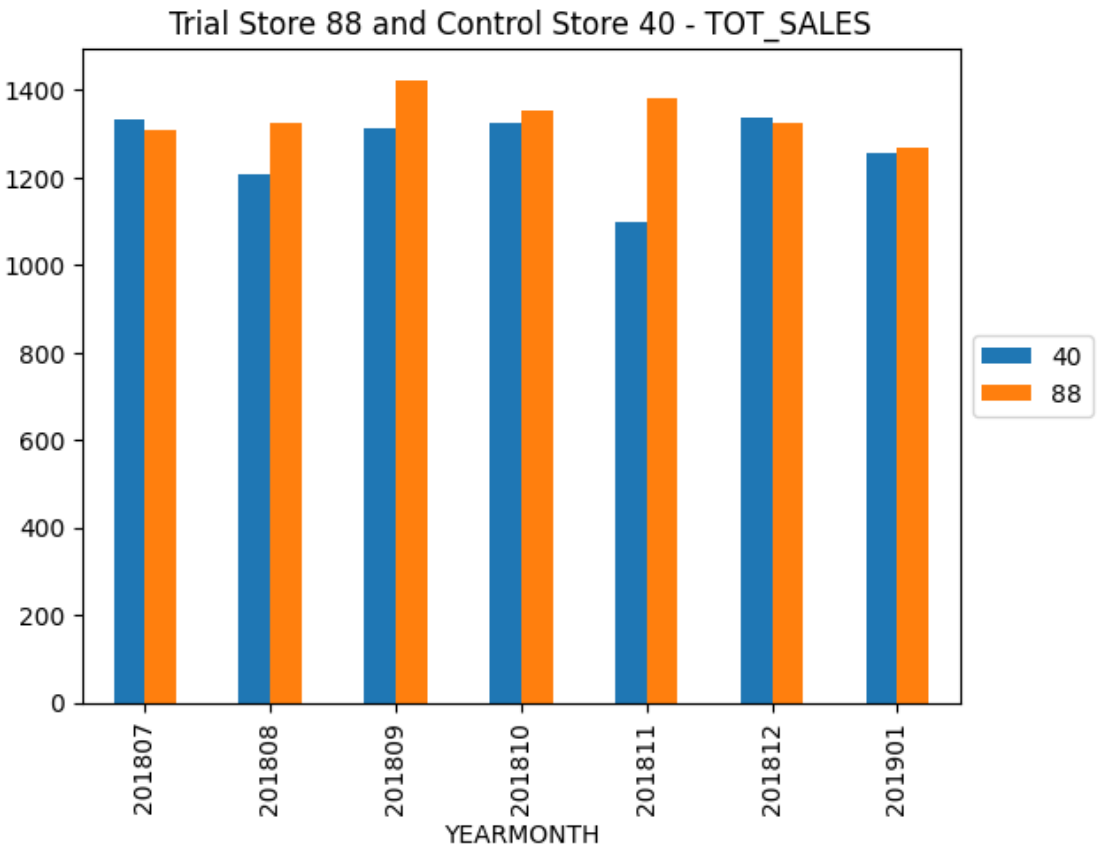
[18]:
```
trial_control_dic = {77:233, 86:155, 88:40}
for key, val in trial_control_dic.items():
    pretrial_full_observ[pretrial_full_observ["STORE_NBR"].isin([key, val])].
 ↪groupby(
        ["YEARMONTH", "STORE_NBR"]).sum()["TOT_SALES"].unstack().plot.bar()
    plt.legend(loc='center left', bbox_to_anchor=(1.0, 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')
```

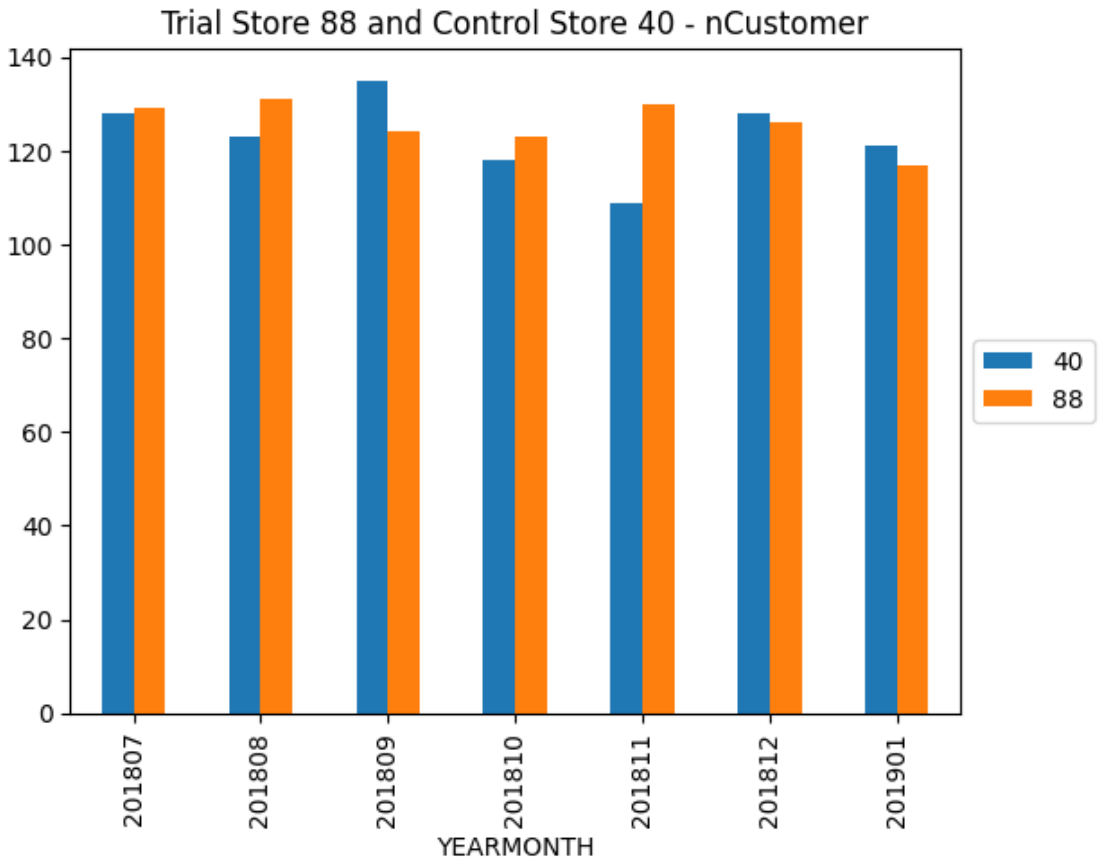

Trial Store 77 and Control Store 233 - TOT_SALES
300
250
200
150
100
50
0
201807
201808
201809
201810
201811
201812
201901
YEARMONTH
77
233


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


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


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

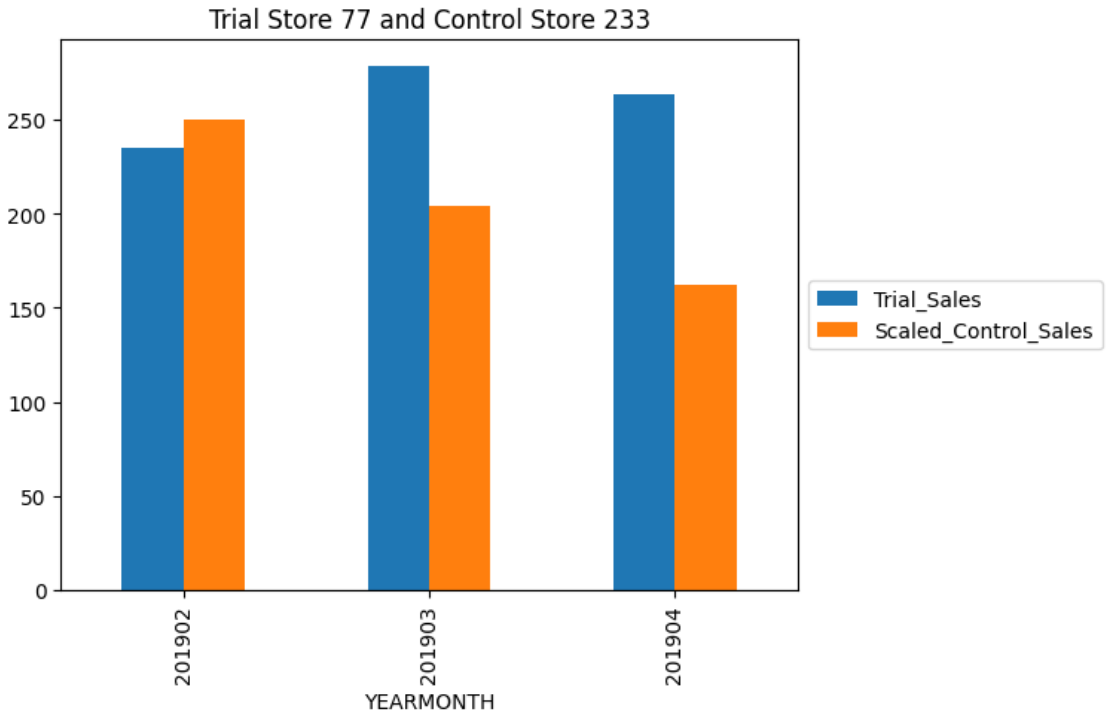


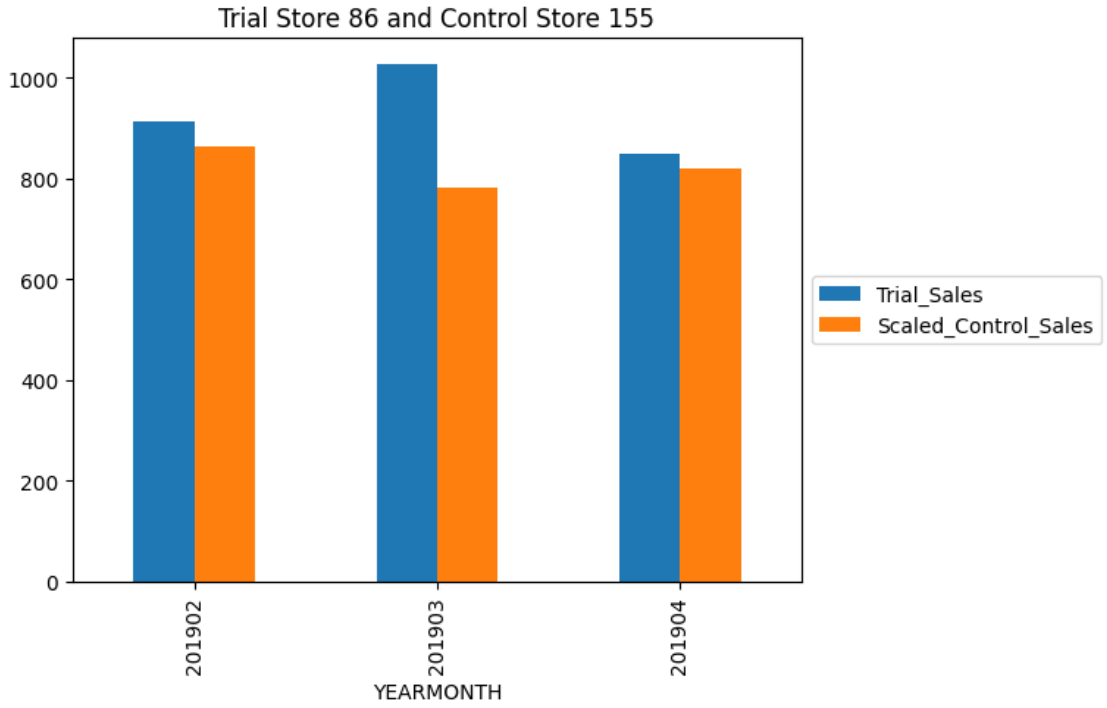
Next we will compare the performance of Trial stores to Control stores during the trial period. To ensure their performance is comparable during Trial period, we need to scale (multiply to ratio of trial/ control) all of Control stores performance to Trial stores performance during pretrial. Starting with ToT_SALES.

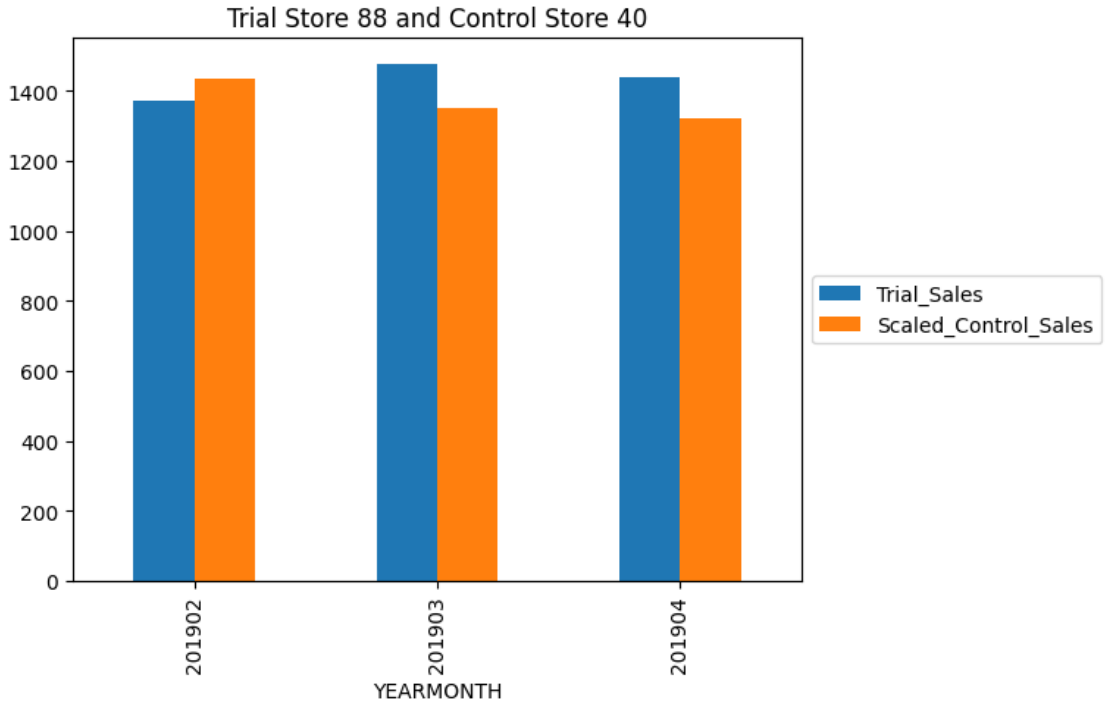
[19]:
```
#Ratio of Store 77 and its Control store.
sales_ratio_77 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] ==␣
 ↪77]["TOT_SALES"].sum() /␣
 ↪pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 233]["TOT_SALES"].
 ↪sum()

#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()
```

[20]:
```
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))
```


Trial Store 77 and Control Store 233
250
200
150
100
50
0
201902
201903
201904
YEARMONTH
Trial_Sales
Scaled_Control_Sales


Trial Store 86 and Control Store 155
1000
800
600
400
200
0
201902
201903
201904
YEARMONTH
Trial_Sales
Scaled_Control_Sales



[21]:
```
percentage_diff
```

[21]:
```
{77: 1.2615468650086281, 86: 1.1315014357363697, 88: 1.043458345854219}
```

[22]:
```
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"]
```

[22]:

	c_STORE_NBR	YEARMONTH	c_ScaledSales	t_STORE_NBR	t_TOT_SALES	\
7	233	201902	249.762622	77	235.0	
8	233	201903	203.802205	77	278.5	
9	233	201904	162.345704	77	263.5	
19	155	201902	864.522060	86	913.2	
20	155	201903	780.320405	86	1026.8	
21	155	201904	819.317024	86	848.2	
31	40	201902	1434.399269	88	1370.2	
32	40	201903	1352.064709	88	1477.2	
33	40	201904	1321.797762	88	1439.4	

	Sales_Percentage_Diff	trial_period
7	-0.060907	trial
8	0.309755	trial
9	0.475075	trial
19	0.054764	trial
20	0.272787	trial
21	0.034642	trial
31	-0.045781	trial
32	0.088458	trial
33	0.085182	trial

Check significance of Trial minus Control stores TOT_SALES Percentage Difference PreTrial vs Trial.

Step 1: Check null hypothesis of 0 difference between control stores Pretrial and Trial period performance.

Step 2: Proof control and trial stores are similar statistically.

Check p-value of control stores Pretrial vs Trial. If$<$ 5 %, it is significantly differnt. 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 Percentage Difference of each Trial month (Feb, March, April 2019). Mean is mean of Percentage Difference during pretrial. Standard deviation is stdev of Percentage Difference during pre trial. Formula is Trial months Percentage Difference minus Mean, divided by Standard deviation. Compare each T-value with 95% significance critical t-value of 6 degrees of freedom (7 months of sample-1).

[28]:
```
from scipy.stats import t, ttest_ind
import numpy as np

# Assuming you have imported the necessary modules and defined your dataframes
```

```
for num in [40, 155, 233]:
    print("Store", num)
    print(ttest_ind(pretrial_scaled_sales_control_stores[pretrial_scaled_sales_control_stores["
    == num]["ScaledSales"],
                    trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["STORE_NBR"]
    == num]["ScaledSales"],
                    equal_var=False), '\n')

alpha = 0.05
degrees_of_freedom =
    min([len(pretrial_scaled_sales_control_stores[pretrial_scaled_sales_control_stores["STORE_N
    == num]),
                             len(trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["STORE_NBR"]
    == num])]) - 1

print("Critical t-value for 95% confidence interval:")
print(t.ppf((alpha/2, 1-alpha/2), df=degrees_of_freedom))
```

```
Store 40
TtestResult(statistic=-0.5958372343168558, pvalue=0.5722861621434027,
df=6.228548324256264)

Store 155
TtestResult(statistic=1.4291956879290917, pvalue=0.1972705865160342,
df=6.794437403919926)

Store 233
TtestResult(statistic=1.191102601097452, pvalue=0.2944500606486209,
df=4.355475642590669)

Critical t-value for 95% confidence interval:
[-4.30265273  4.30265273]
```

[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 isnt any statistically significant difference between control store's scaled Pre trial and Trial period saled.

[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["STORE_NBR"] ==␣
 ↪trial]["TOT_SALES"],
                    ␣
 ↪pretrial_scaled_sales_control_stores[pretrial_scaled_sales_control_stores["STORE_NBR"]␣
 ↪== cont]["ScaledSales"],
                    equal_var=True), '\n')
    #print(len(pretrial_full_observ[pretrial_full_observ["STORE_NBR"] ==␣
 ↪trial]["TOT_SALES"]),len(pretrial_scaled_sales_control_stores[pretrial_scaled_sales_control
 ↪== 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
TtestResult(statistic=-1.2533353315065932e-15, pvalue=0.999999999999999,
df=12.0)

Trial store: 86 , Control store: 155
TtestResult(statistic=3.1048311203382156e-15, pvalue=0.9999999999999976,
df=12.0)

Trial store: 88 , Control store: 40
TtestResult(statistic=-5.69358613974361e-15, pvalue=0.9999999999999956, df=12.0)

Critical t-value for 95% confidence interval:
[-2.44691185  2.44691185]
```

Null hypothesis is true. There isnt any statistically significant difference between Trial stores sales and Control stores scaled sales performance during pre trial.

[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():
```

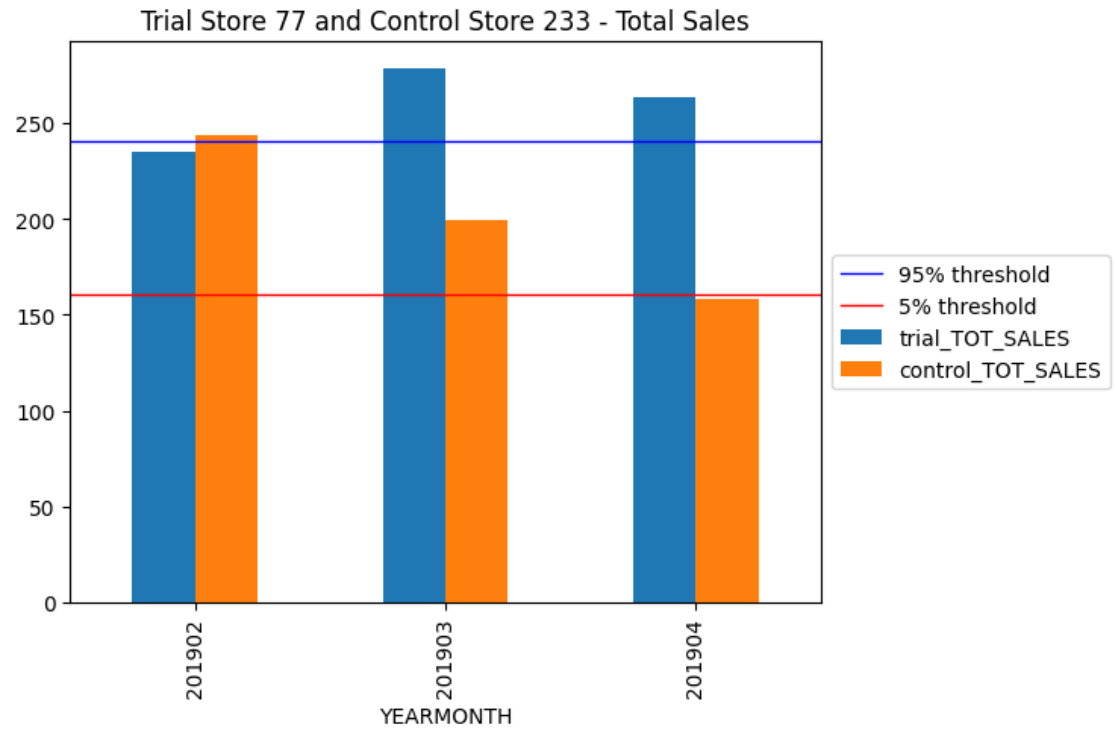
```
        pdif = scaledsales_vs_trial[(scaledsales_vs_trial["YEARMONTH"] ==␣
 ↪t_month) & (scaledsales_vs_trial["t_STORE_NBR"] ==␣
 ↪trial)]["Sales_Percentage_Diff"]
        print(t_month,":",(float(pdif)-mean)/std)
    print('\n')

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

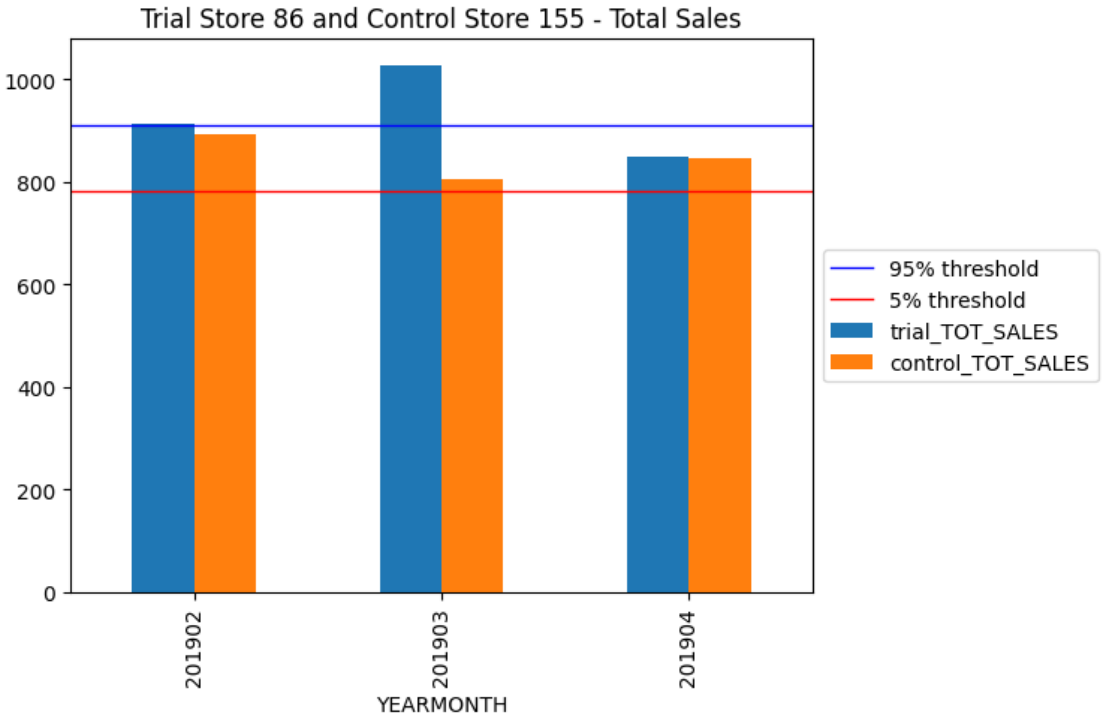
```
Trial store: 77 , Control store: 233
201902 : -0.7171038288055838
201903 : 3.035317928855674
201904 : 4.708944418758219


Trial store: 86 , Control store: 155
201902 : 1.4133618775921597
201903 : 7.123063846042147
201904 : 0.8863824572944234


Trial store: 88 , Control store: 40
201902 : -0.5481633746817577
201903 : 1.0089992743637823
201904 : 0.9710006270463672


Critical t-value for 95% confidence interval:
1.9431802803927816

<ipython-input-31-613a6b327476>:10: FutureWarning: Calling float on a single
element Series is deprecated and will raise a TypeError in the future. Use
float(ser.iloc[0]) instead
  print(t_month,":",(float(pdif)-mean)/std)
```

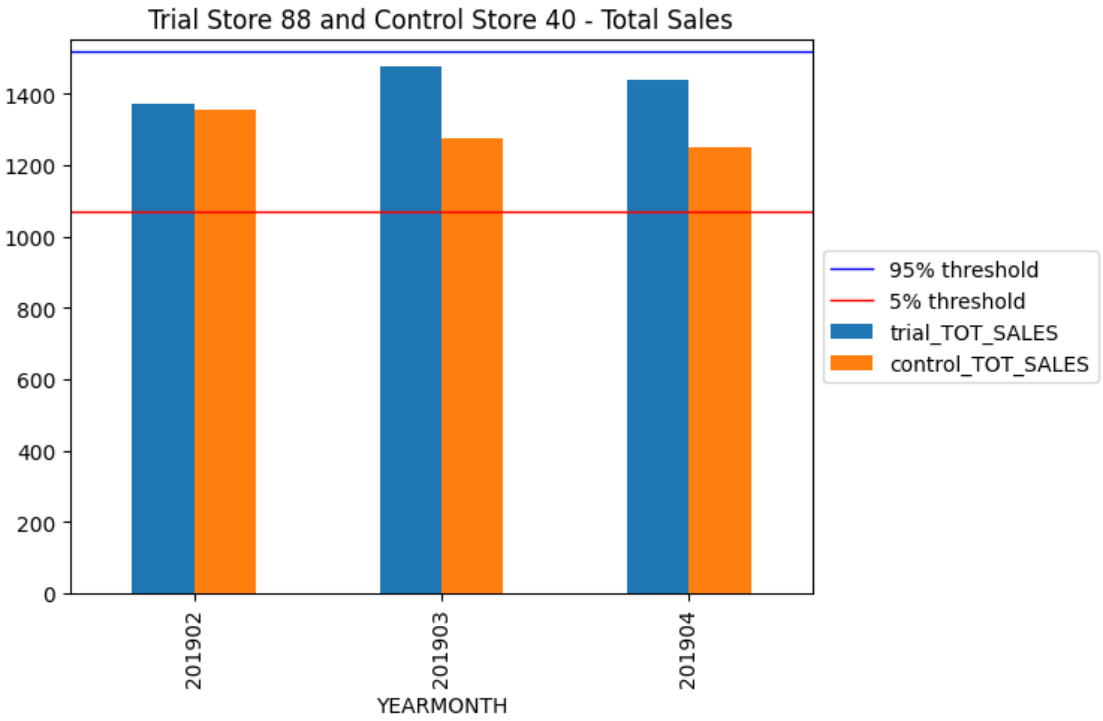
There are 3 monthes increase in performance that are statistically significant (Above the 95% confidence interval t-score): March and April trial months for trial store 77. March trial months for trial store 86.

[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")
```



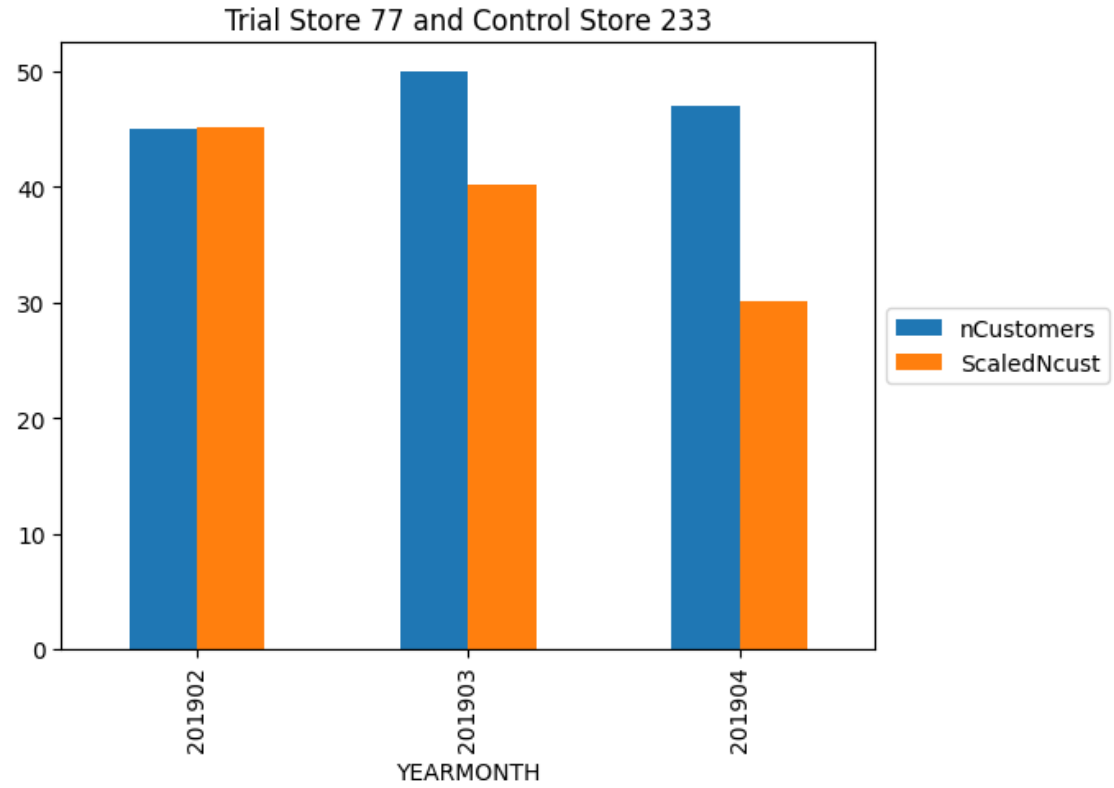

Trial Store 86 and Control Store 155 - Total Sales
1000
800
600
400
200
0
201902
201903
201904
YEARMONTH
95% threshold
5% threshold
trial_TOT_SALES
control_TOT_SALES

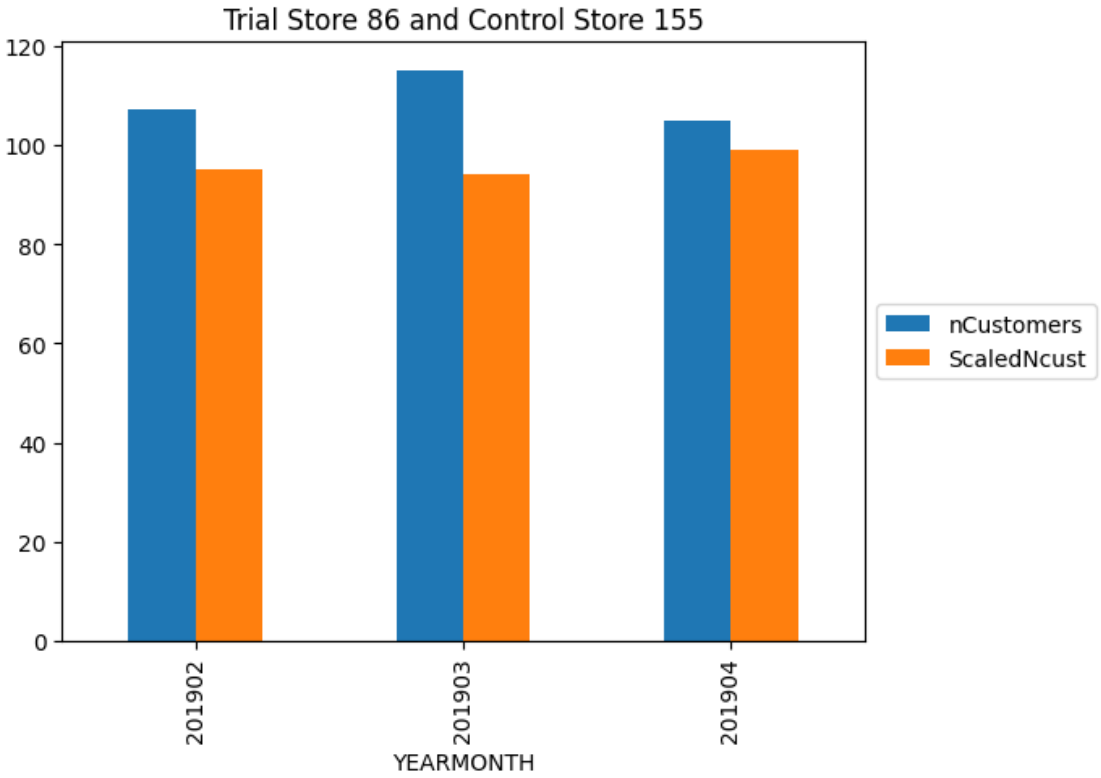

Trial Store 88 and Control Store 40 - Total Sales
1400
1200
1000
800
600
400
200
0
201902
201903
201904
YEARMONTH
95% threshold
5% threshold
trial_TOT_SALES
control_TOT_SALES

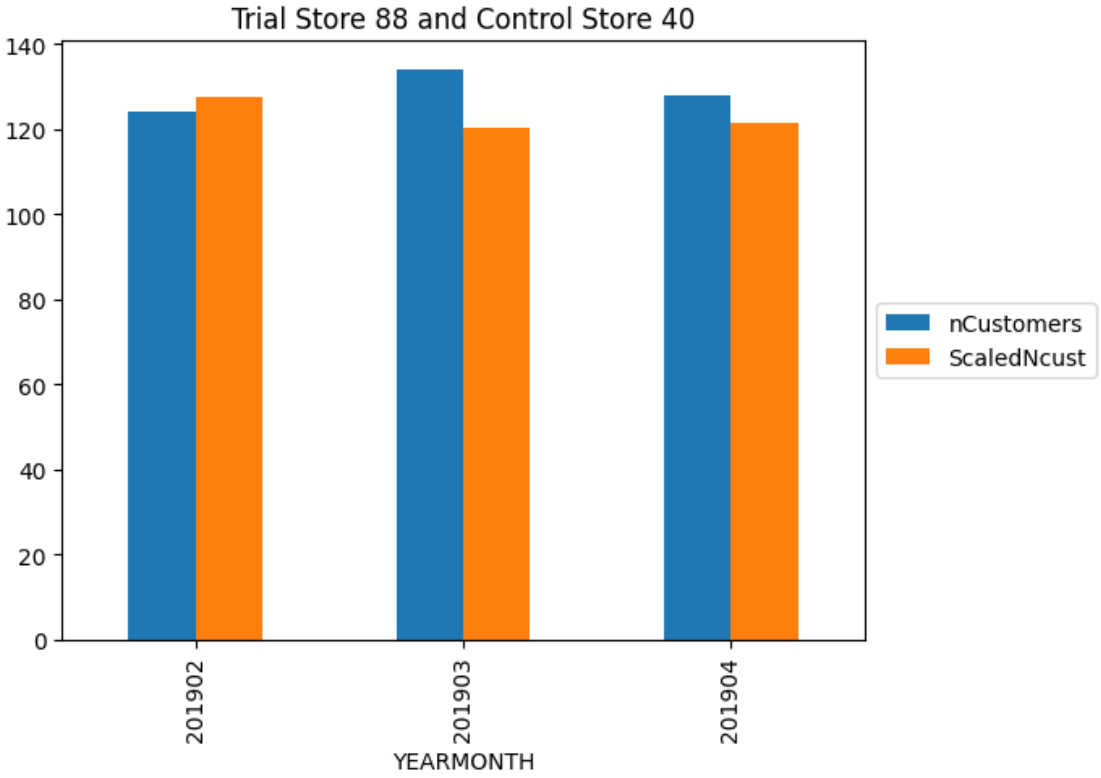
[33]:
```
#Ratio of Store 77 and its Control store.
ncust_ratio_77 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] ==␣
↪77]["nCustomers"].sum() /␣
↪pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 233]["nCustomers"].
↪sum()

#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()
```

[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["YEARMONTH"] >=␣
↪201902) & (scaled_ncust_control_stores["YEARMONTH"] <= 201904)]
pretrial_scaled_ncust_control_stores =␣
↪scaled_ncust_control_stores[scaled_ncust_control_stores["YEARMONTH"] <␣
↪201902]

ncust_percentage_diff = {}

for trial, control in trial_control_dic.items():
```

```
   a =␣
↪trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["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("YEARMONTH").
↪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 86 and Control Store 155
120
100
80
60
40
20
0
201902
201903
201904
YEARMONTH
nCustomers
ScaledNcust


Trial Store 88 and Control Store 40
140
120
100
80
60
40
20
0
201902
201903
201904
YEARMONTH
nCustomers
ScaledNcust

[35]:
```
ncust_percentage_diff
```

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

[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"]
```

[36]:

	c_STORE_NBR	YEARMONTH	c_ScaledNcust	t_STORE_NBR	t_nCustomers	\
7	233	201902	45.151007	77	45	
8	233	201903	40.134228	77	50	
9	233	201904	30.100671	77	47	
19	155	201902	95.000000	86	107	
20	155	201903	94.000000	86	115	
21	155	201904	99.000000	86	105	
31	40	201902	127.610209	88	124	
32	40	201903	120.464037	88	134	
33	40	201904	121.484919	88	128	

	nCust_Percentage_Diff	trial_period
7	-0.003350	trial
8	0.218913	trial
9	0.438370	trial
19	0.118812	trial
20	0.200957	trial
21	0.058824	trial
31	-0.028697	trial
32	0.106388	trial
33	0.052228	trial

Check significance of Trial minus Control nCustomers Percentage Difference PreTrial vs Trial.

Step 1: Check null hypothesis of 0 difference between control stores Pretrial 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 pretrial is the same as during trial.

[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["
  ↪== 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["STOR
  ↪== num]),
                        ␣
  ↪len(trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["STORE_NBR"]␣
  ↪== num])])-1))
```

```
Store 40
TtestResult(statistic=0.644732693420032, pvalue=0.5376573016017127,
df=7.7735551763644395)

Store 155
TtestResult(statistic=1.3888888888888882, pvalue=0.204345986327886,
df=7.572528547077964)

Store 233
TtestResult(statistic=0.8442563765225701, pvalue=0.4559280037660254,
df=3.2638055826510652)

Critical t-value for 95% confidence interval:
[-4.30265273  4.30265273]
```

[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
TtestResult(statistic=0.0, pvalue=1.0, df=12.0)

Trial store: 86 , Control store: 155
TtestResult(statistic=0.0, pvalue=1.0, df=12.0)

Trial store: 88 , Control store: 40
TtestResult(statistic=-7.648483953264653e-15, pvalue=0.999999999999994, df=12.0)

Critical t-value for 95% confidence interval:
[-2.44691185  2.44691185]
```

[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)
```

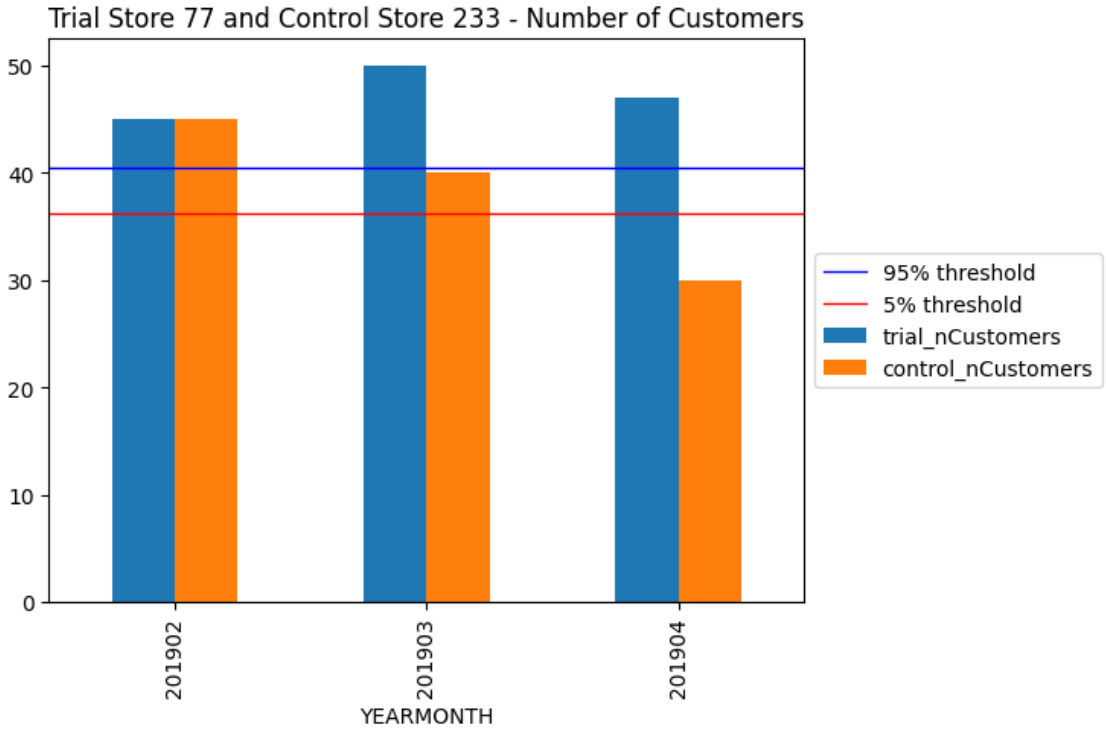
```
Trial store: 77 , Control store: 233
201902 : -0.19886295797440687
201903 : 8.009609025380932
201904 : 16.114474772873923
```

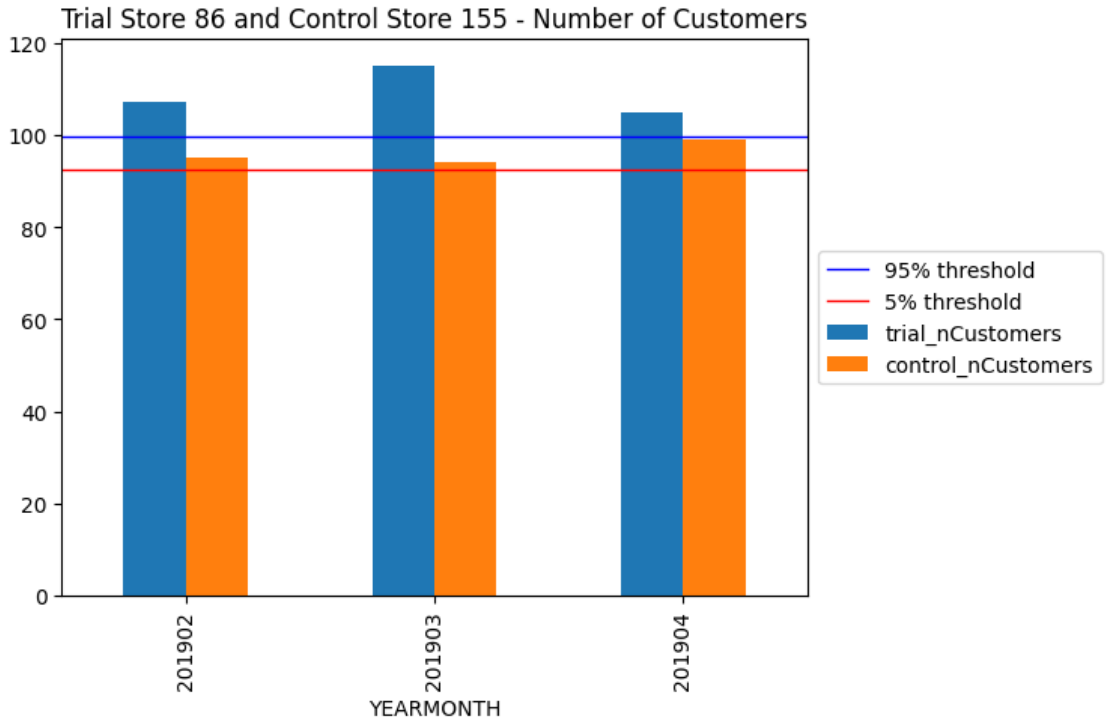
```
Trial store: 86 , Control store: 155
201902 : 6.220524882227514
201903 : 10.52599074274189
201904 : 3.0763575852842706


Trial store: 88 , Control store: 40
201902 : -0.3592881735131531
201903 : 1.2575196020616801
201904 : 0.6092905590514273


Critical t-value for 95% confidence interval:
1.9431802803927816

<ipython-input-39-ab71f75d2657>:10: FutureWarning: Calling float on a single
element Series is deprecated and will raise a TypeError in the future. Use
float(ser.iloc[0]) instead
  print(t_month,":",(float(pdif)-mean)/std)
```

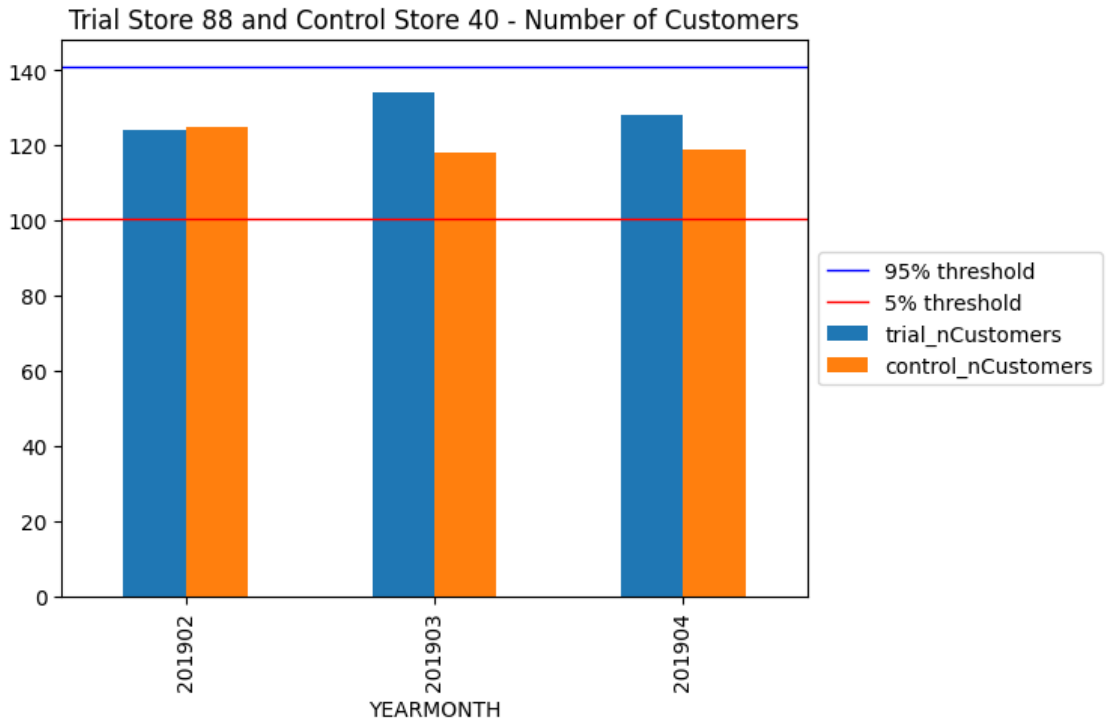
There are 5 months increase in performance that are statistically significant (Above the 95% confidence interval t-score): March and April trial months for trial store 77. Feb, March and April trial months for trial store 86.

[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 duirng trial period. But not for trial store 88. Perhaps the client knows if theres anything about trial 88 that differs it from the other two trial.
5. Overall the trial showed positive significant result.