Name - Mayank Yadav

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

Importing Necessary Libraries

In [1]:
```python
import pandas as pd
import numpy as np

# for data visualization
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

Importing Dataset

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

Out[2]:

	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	SI
1	1002	2018-09-16	1	2	58	Red Rock Deli Chikn&Garlic Aioli 150g	1	2.7	150	RRD	SI
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	SI

Data Exploration

In [3]:
```python
print("Number of Rows and Columns :- ", qvi.shape)
```

```
Number of Rows and Columns :- (264834, 12)
```

In [4]:
```python
# Basic Information of dataset
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
```

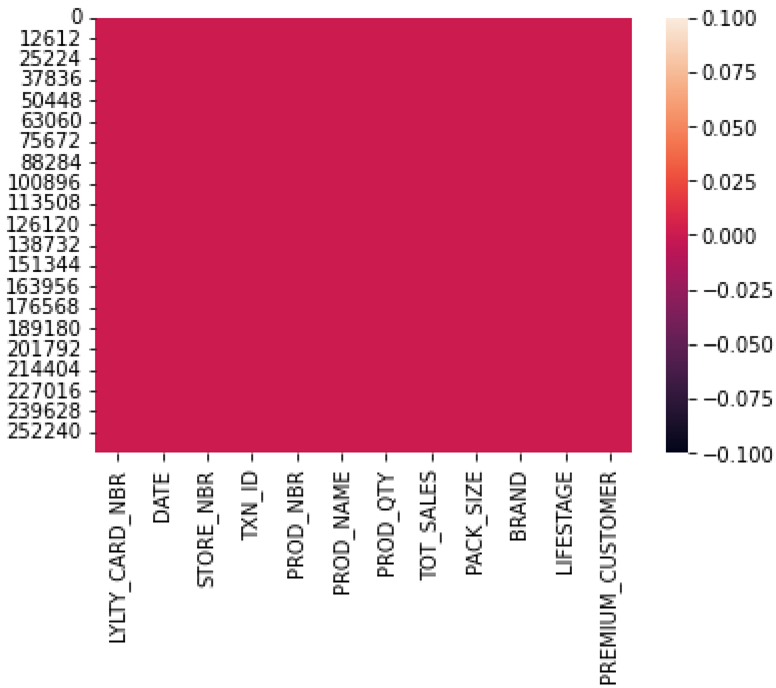
In [5]:
```
# Statistical Summary of QVI_data
qvi.describe().T
```

Out[5]:

	count	mean	std	min	25%	50%	75%	max
LYLTY_CARD_NBR	264834.0	135548.793331	80579.898912	1000.0	70021.0	130357.0	203094.00	2373711.0
STORE_NBR	264834.0	135.079423	76.784063	1.0	70.0	130.0	203.00	272.0
TXN_ID	264834.0	135157.623236	78132.920436	1.0	67600.5	135136.5	202699.75	2415841.0
PROD_NBR	264834.0	56.583554	32.826444	1.0	28.0	56.0	85.00	114.0
PROD_QTY	264834.0	1.905813	0.343436	1.0	2.0	2.0	2.00	5.0
TOT_SALES	264834.0	7.299346	2.527241	1.5	5.4	7.4	9.20	29.5
PACK_SIZE	264834.0	182.425512	64.325148	70.0	150.0	170.0	175.00	380.0

Checking missing values in Dataset

In [6]:
```
sns.heatmap(qvi.isnull())
plt.show()
```



In [7]:
```
qvi.isnull().sum()
```

Out[7]:
```
LYLTY_CARD_NBR      0
DATE                0
STORE_NBR           0
TXN_ID              0
PROD_NBR            0
PROD_NAME           0
PROD_QTY            0
TOT_SALES           0
PACK_SIZE           0
BRAND               0
LIFESTAGE           0
PREMIUM_CUSTOMER    0
dtype: int64
```

❖ We can see there is no missing values the dataset.

In [8]:
```
### Handling "Date" column
qvi["DATE"] = pd.to_datetime(qvi["DATE"])
qvi["YEARMONTH"] = qvi["DATE"].dt.strftime("%Y%m").astype("int")
```

Compile each store's monthly:-

- Total sales
- Number of customers
- Average transactions per customer
- Average chips per customer
- Average price per unit

In [9]:
```
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 [10]:
```
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
```

Pre-Trial Observation as this filter only stores with full 12 months observation

In [11]:
```python
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[11]:

	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 [12]:
```python
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 [13]:
```python
corr_table = pd.DataFrame()
for trial_num in [77, 86, 88]:
    corr_table = pd.concat([corr_table, calcCorrTable(["TOT_SALES", "nCustomers", "nTxnPerCust", "nChipsPerTxn",

corr_table.head(8)
```

Out[13]:

	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 [14]:
```python
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] - input
        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 [15]:
```
dist_table = pd.DataFrame()
for trial_num in [77, 86, 88]:
    dist_table = pd.concat([dist_table, calculateMagnitudeDistance(["TOT_SALES", "nCustomers", "nTxnPerCust", "n

dist_table.head(8)
dist_table
```

Out[15]:

	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 [16]:
```
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 [17]:
```python
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 [18]:
```python
corr_weight = 0.5
dist_weight = 1 - corr_weight
```

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

In [19]:
```python
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
for trial_num in compare_metrics_table1["Trial_Str"].unique():
    print(grouped_comparison_table1[grouped_comparison_table1["Trial_Str"] == trial_num].sort_values(ascending=F
```

```
     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 [20]:
```
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 [21]:
```
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
for trial_num in compare_metrics_table2["Trial_Str"].unique():
    print(grouped_comparison_table2[grouped_comparison_table2["Trial_Str"] == trial_num].sort_values(ascending=F
```

```
     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 [22]:
```python
for trial_num in compare_metrics_table2["Trial_Str"].unique():
    a = grouped_comparison_table1[grouped_comparison_table1["Trial_Str"] == trial_num].sort_values(ascending=Fal b
    =  grouped_comparison_table2[grouped_comparison_table2["Trial_Str"]  ==  trial_num].sort_values(ascending=Fal
    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:

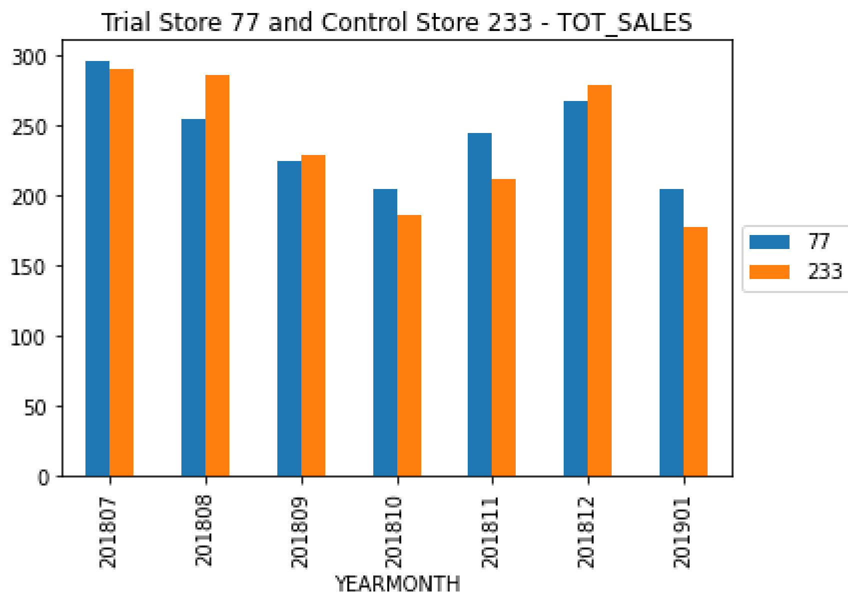
1. Trial store 77: Store 233, 41, 111
2. Trial store 86: Store 155, 225, 109
3. Trial store 88: Store 237, 203, 40

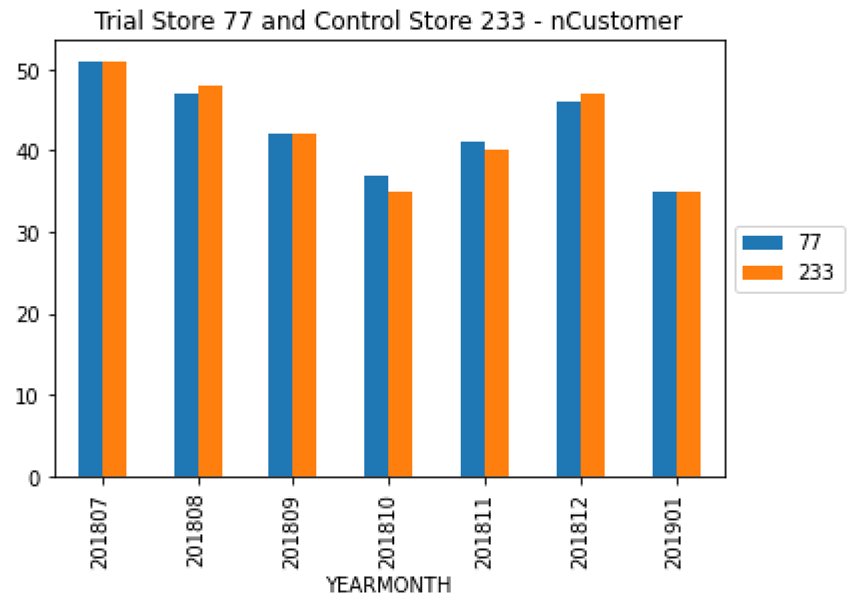
Final SImilarities based on Highest average of both features combined:

1. Trial store 77: Store 233
2. Trial store 86: Store 155

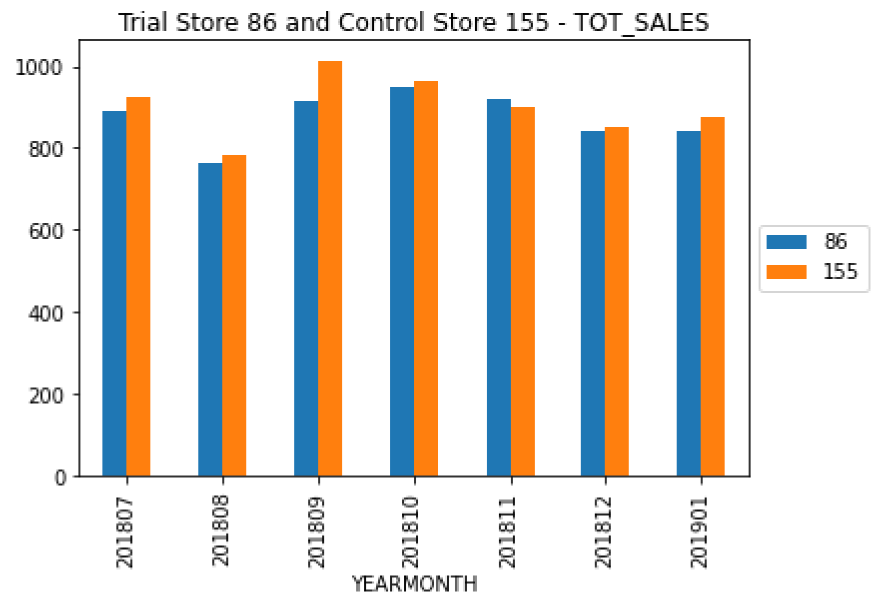
3. Trial store 88: Store 40

In [23]:
```
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')
```

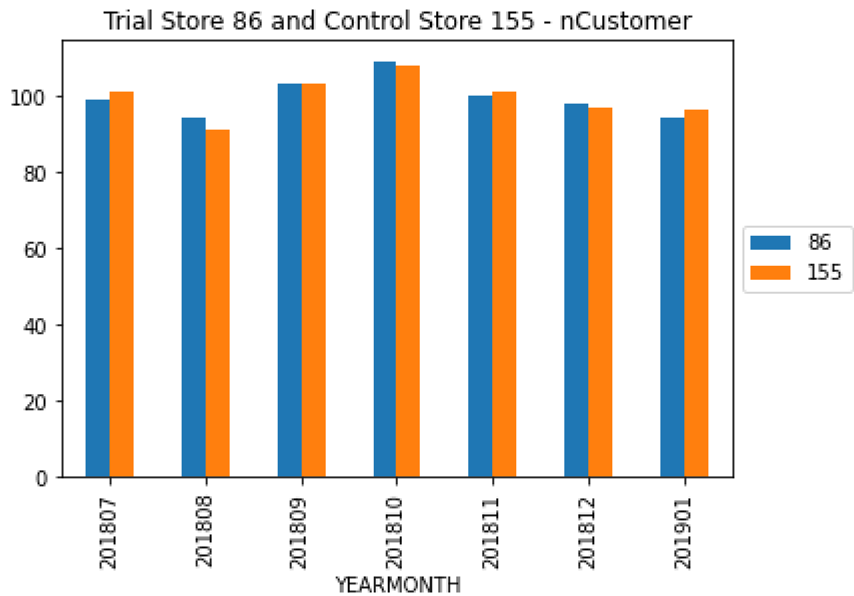


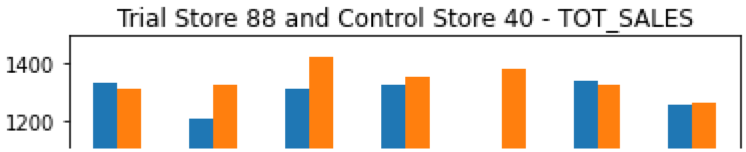


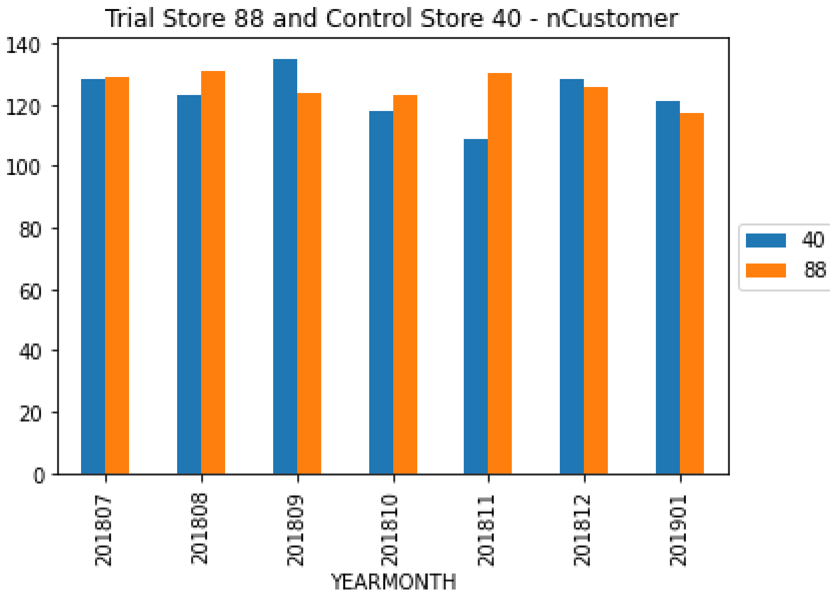
Trial Store 77 and Control Store 233 - nCustomer
50
40
30
20
10
0
201807
201808
201809
201810
201811
201812
201901
YEARMONTH
77
233



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

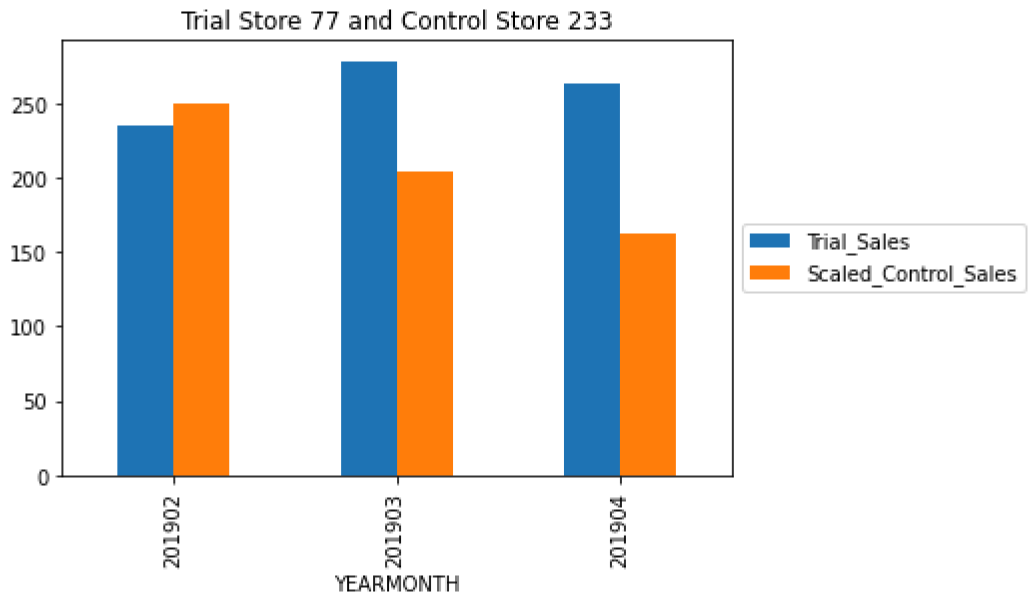

Trial Store 88 and Control Store 40 - nCustomer
140
120
100
80
60
40
20
0
201807
201808
201809
201810
201811
201812
201901
YEARMONTH
40
88

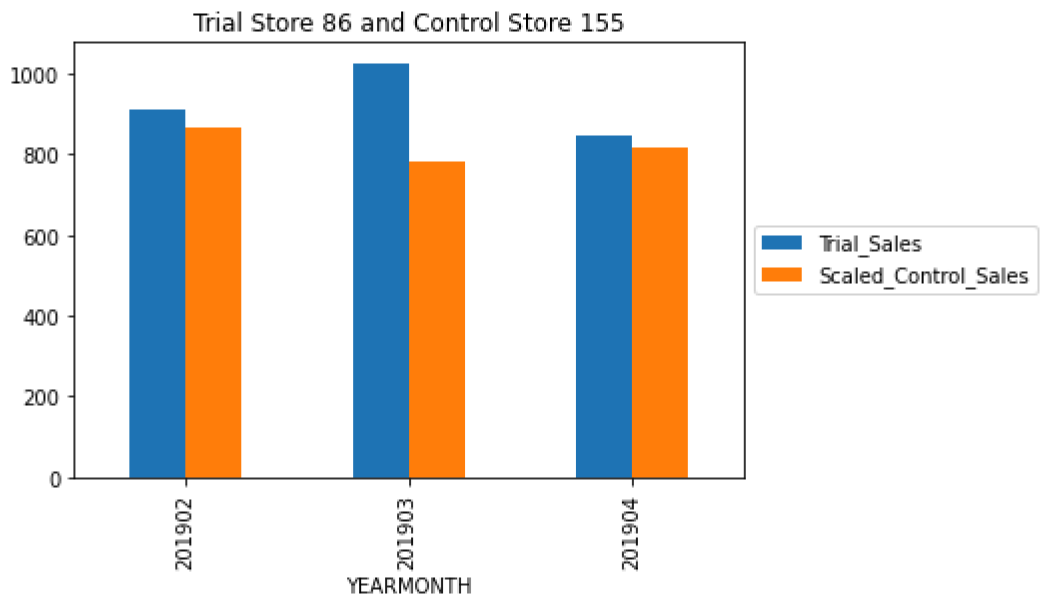
•♦• Next we'll compare the performance of Trial stores to Control stores during the trial period. To ensure their performance is comparable during Trial period, we need to scale (multiply to ratio of trial / control) all of Control stores' performance to Trial store's performance during pre-trial. Starting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

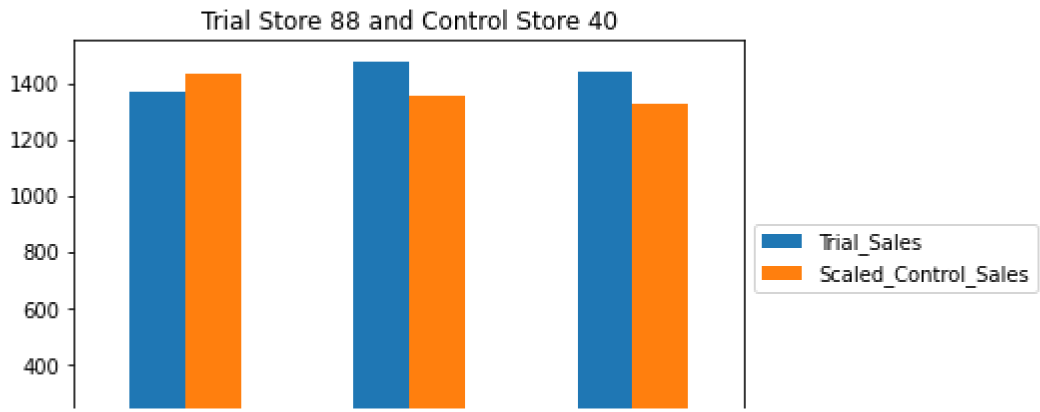
In [24]:
```
#Ratio of Store 77 and its Control store.
sales_ratio_77 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 77]["TOT_SALES"].sum() / pretrial_ful

#Ratio of Store 86 and its Control store.
sales_ratio_86 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 86]["TOT_SALES"].sum() / pretrial_ful

#Ratio of Store 77 and its Control store.
sales_ratio_88 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 88]["TOT_SALES"].sum() / pretrial_ful
```

In [25]:

```
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", "YEARMONT

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"] >= 201
pretrial_scaled_sales_control_stores = scaled_sales_control_stores[scaled_sales_control_stores["YEARMONTH"] < 20

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").r
    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



In [26]:
```
percentage_diff
```

Out[26]:
```
{77: 1.2615468650086281, 86: 1.1315014357363697, 88: 1.0434583458542l9}
```

```
In [27]: temp1 = scaled_sales_control_stores.sort_values(by=["STORE_NBR", "YEARMONTH"], ascending=[False, True]).reset_in
temp2 = full_observ[full_observ["STORE_NBR"].isin([77,86,88])][["STORE_NBR", "YEARMONTH", "TOT_SALES"]].reset_in
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_S 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_scaled_sales_control_stores["STORE_NBR"] == nu
    trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["STORE_NBR"] == num]["Sca
    equal_var=False), '\n')
    #print(len(pretrial_scaled_sales_control_stores[pretrial_scaled_sales_control_stores["STORE_NBR"] == num]["S

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
len(trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["STORE_NBR"] == n
```

```
Store 40
Ttest_indResult(statistic=-0.5958372343168558, pvalue=0.5722861621434027)

Store 155
Ttest_indResult(statistic=1.4291956879290917, pvalue=0.1972705865160342)

Store 233
Ttest_indResult(statistic=1.1911026010974521, pvalue=0.2944500606486209)

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]:
```python
# 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"] == con
                    equal_var=True), '\n')
    #print(len(pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == trial]["TOT_SALES"]),len(pretrial_scale

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=-1.2533353315065932e-15, pvalue=0.9999999999999999)

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

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

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
    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_ST
        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)
```

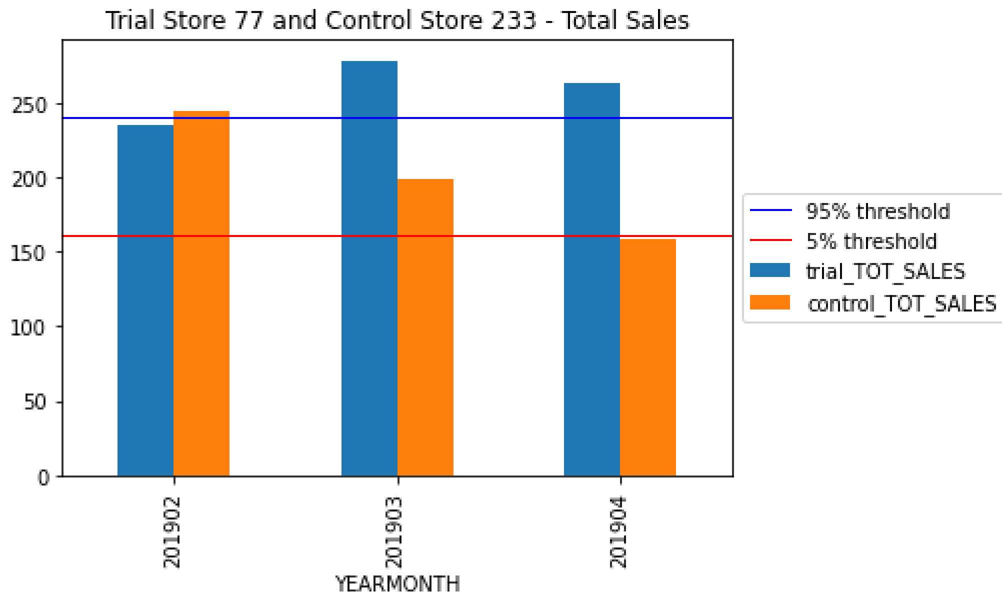
```
Trial store: 77 , Control store: 233
201902 : -0.7171038288055838 201903 :
3.035317928855674 201904 :
4.708944418758219


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:
1.9431802803927818
```

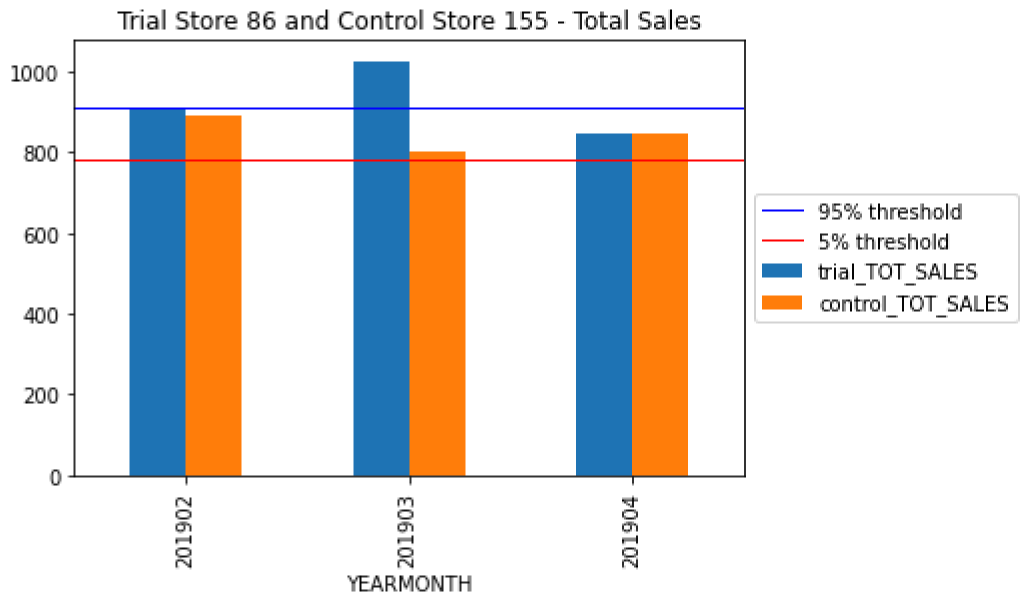
There are 3 months' increase in performance that are statistically significant (Above the 95% confidence interval t-score):

March and April trial months for trial store 77

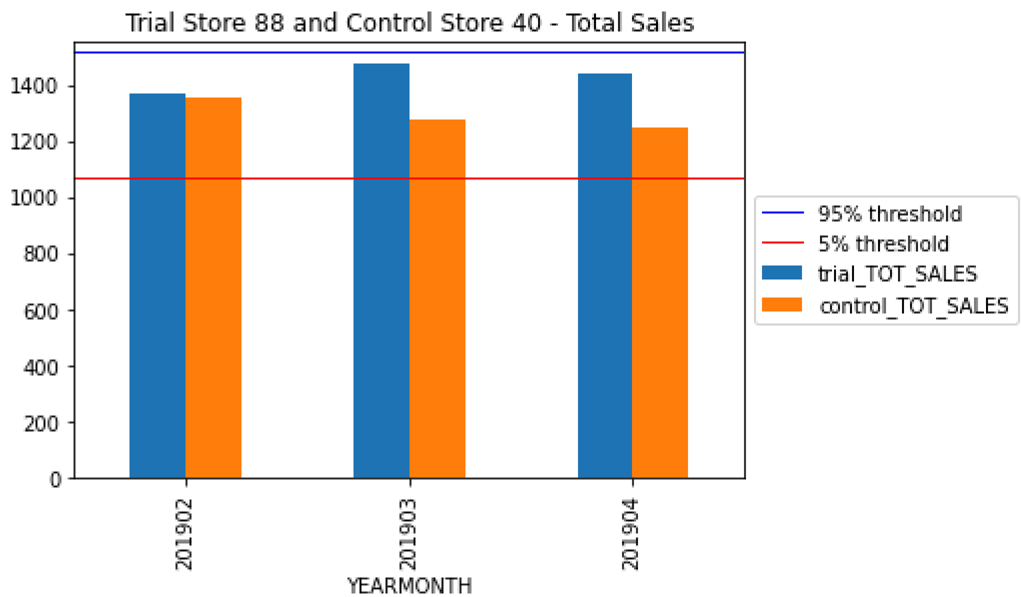
March trial months for trial store 86

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(colu b
    = trial_full_observ[trial_full_observ["STORE_NBR"] == trial][["STORE_NBR", "YEARMONTH", "TOT_SALES"]].rena
    comb = b[["YEARMONTH", "trial_TOT_SALES"]].merge(a[["YEARMONTH", "control_TOT_SALES"]],on="YEARMONTH").set_i
    comb.plot.bar()                                              cont_sc_sales                                   =
    trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["STORE_NBR"]    ==    control]    std    =
    scaledsales_vs_trial[(scaledsales_vs_trial["c_STORE_NBR"]   ==   control)   &   (scaledsales_vs_trial["trial_p
    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")
```





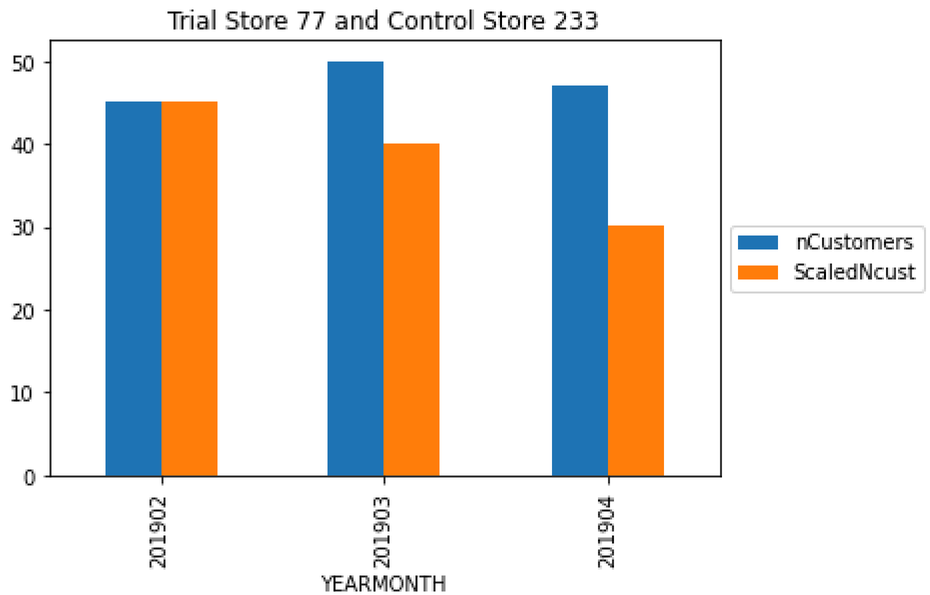
Trial Store 86 and Control Store 155 - Total Sales
1000
800
600
400
200
0
201902
201903
201904
YEARMONTH
95% threshold
5% threshold
trial_TOT_SALES
control_TOT_SALES

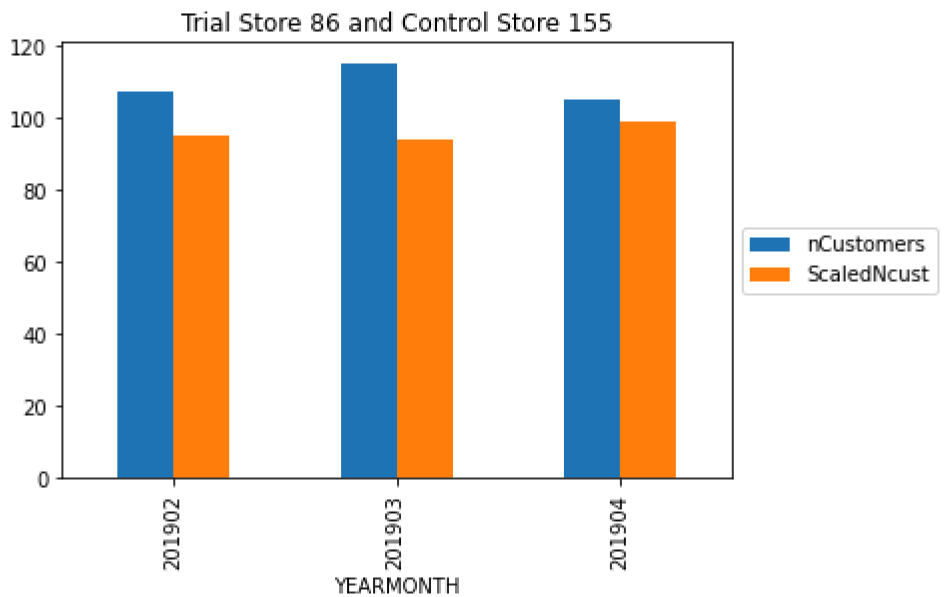


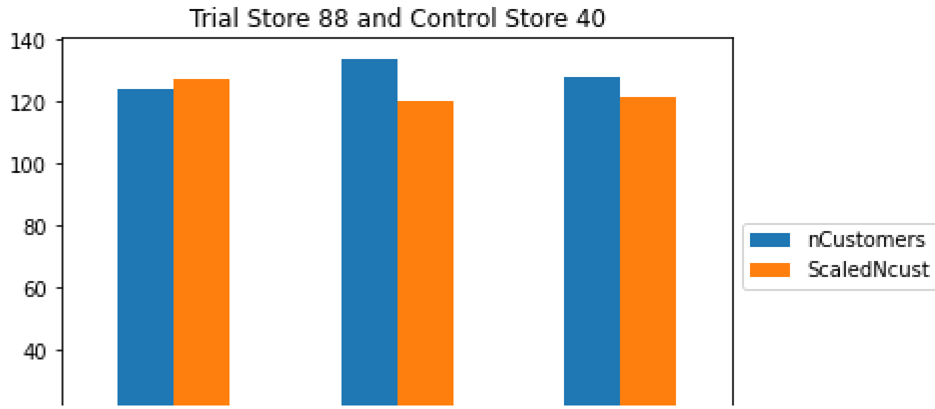
Trial Store 88 and Control Store 40 - Total Sales
1400
1200
1000
800
600
400
200
0
201902
201903
201904
YEARMONTH
95% threshold
5% threshold
trial_TOT_SALES
control_TOT_SALES

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_fu

#Ratio of Store 86 and its Control store.
ncust_ratio_86 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 86]["nCustomers"].sum() / pretrial_fu

#Ratio of Store 77 and its Control store.
ncust_ratio_88 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 88]["nCustomers"].sum() / pretrial_fu
```

In [34]:
```python
#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", "YEARMONT

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"]  >=  201
pretrial_scaled_ncust_control_stores = scaled_ncust_control_stores[scaled_ncust_control_stores["YEARMONTH"] < 20

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").
    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
201902
201903
201904
YEARMONTH
nCustomers
ScaledNcust


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



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_in
temp2 = full_observ[full_observ["STORE_NBR"].isin([77,86,88])][["STORE_NBR", "YEARMONTH", "nCustomers"]].reset_i
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_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]:
```python
# 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"] == nu
    trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["STORE_NBR"] == num]["Sca
    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
len(trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["STORE_NBR"] == n
```

```
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"] == con
                   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=0.999999999999994)

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
    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_ST
        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)
```

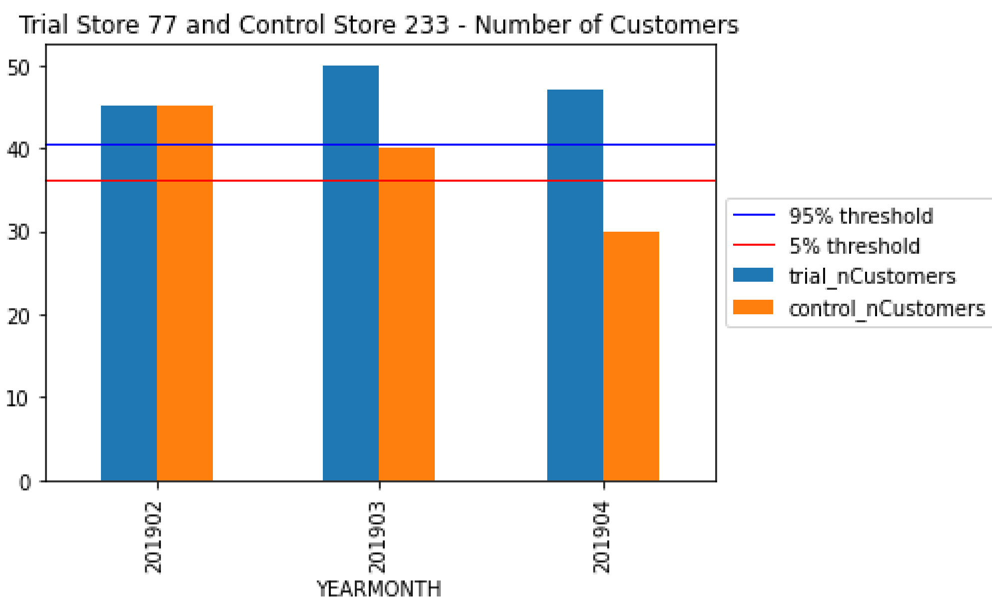
```
Trial store: 77 , Control store: 233
201902 : -0.19886295797440687
201903 : 8.009609025380932
201904 : 16.114474772873923



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:
1.9431802803927818
```

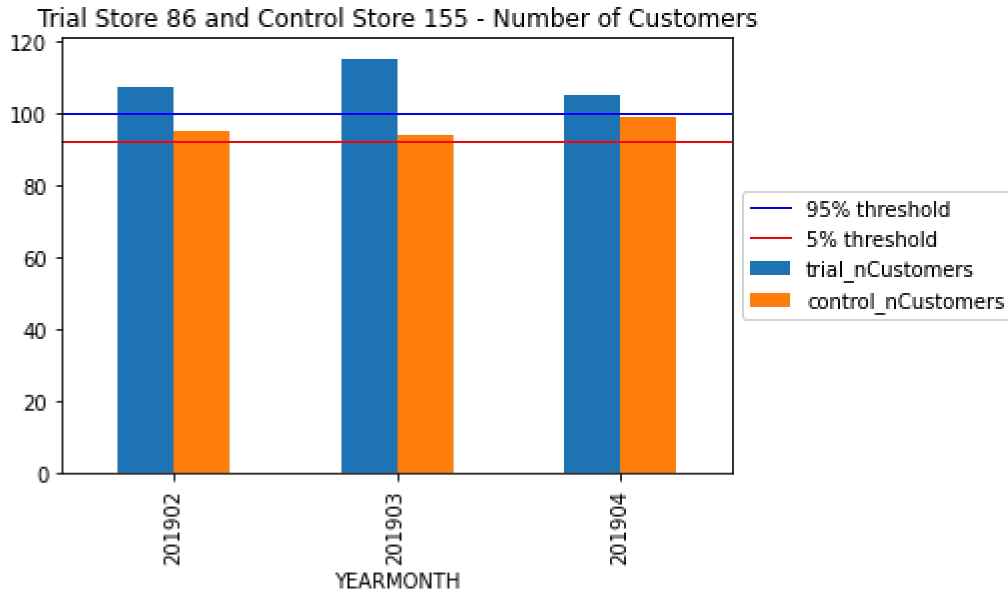
There are 5 months' increase in performance that are statistically significant (Above the 95% confidence interval t-score):

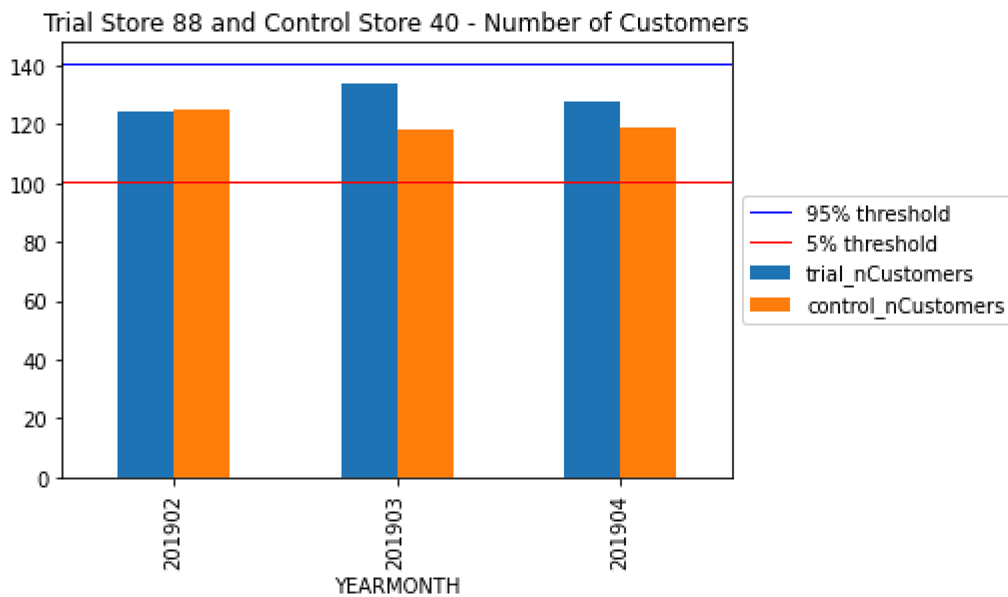
March and April trial months for trial store 77

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(colu b
    = trial_full_observ[trial_full_observ["STORE_NBR"] == trial][["STORE_NBR", "YEARMONTH", "nCustomers"]].ren
    comb = b[["YEARMONTH", "trial_nCustomers"]].merge(a[["YEARMONTH", "control_nCustomers"]],on="YEARMONTH").set
    comb.plot.bar()                                                         cont_sc_ncust                      =
    trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["STORE_NBR"]    ==    control]    std    =
    scaledncust_vs_trial[(scaledncust_vs_trial["c_STORE_NBR"]    ==    control)    &    (scaledncust_vs_trial["trial_p
    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")
```







Insights :-

•◆• 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.

•♦• Trial store 77: Control store 233 •♦• Trial store 86: Control store 155 •♦• Trial store 88: Control store 40 •♦• 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.
•♦• Overall the trial showed positive significant result.

••♦•••♦••