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

In [2]:
```
QVI = pd.read_csv('QVI_data.csv')
```

In [3]:
```
QVI.head()
```

Out[3]:

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TO
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	

In [4]:
```
QVI.describe()
```

Out[4]:

	LYLTY_CARD_NBR	STORE_NBR	TXN_ID	PROD_NBR	PROD_QTY	TOT_S
count	2.648340e+05	264834.000000	2.648340e+05	264834.000000	264834.000000	264834.0
mean	1.355488e+05	135.079423	1.351576e+05	56.583554	1.905813	7.2
std	8.057990e+04	76.784063	7.813292e+04	32.826444	0.343436	2.5
min	1.000000e+03	1.000000	1.000000e+00	1.000000	1.000000	1.5
25%	7.002100e+04	70.000000	6.760050e+04	28.000000	2.000000	5.4
50%	1.303570e+05	130.000000	1.351365e+05	56.000000	2.000000	7.4
75%	2.030940e+05	203.000000	2.026998e+05	85.000000	2.000000	9.2
max	2.373711e+06	272.000000	2.415841e+06	114.000000	5.000000	29.5

Total Sales

In [5]:
```
sum(QVI['TOT_SALES'])
```

Out[5]: 1933114.9999996515

There customer column so I have taken TXN_ID as it is unique

In [6]:
```
Total_customer = 241584
```

Total number of Transaction per customer

In [7]:
```
QVI.shape
```

Out[7]: (264834, 12)

In [8]:
```
Average_Transaction = Total_customer/264834
```

In [9]:
```
Average_Transaction
```

Out[9]: 0.9122091574344684

We will be examining the performance in trial vs control stores to provide a recommendation for each location based on our insight.

A) Select control stores – explore the data and define metrics for control store selection – "What would make them a control store?" Visualize the drivers to see suitability.

B) Assessment of the trial – get insights of each of the stores. Compare each trial store with ontrol store to get its overall performance. We want to know if the trial stores were successful or not.

C) Collate findings – summarise findings for each store and provide recommendations to share with client outlining the impact on sales during trial period.

In [11]:
```
QVI["DATE"] = pd.to_datetime(QVI["DATE"])
QVI["YEARMONTH"] = QVI["DATE"].dt.strftime("%Y%m").astype("int")
```

Compiling each stores monthly

In [12]:
```
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_chi
ps_price]
    metrics = pd.concat(aggregates, axis=1)
    metrics.columns = ["TOT_SALES", "nCustomers", "nTxnPerCust", "nChipsPerTx
n", "avgPricePerUnit"]
    return metrics
```

In [13]:
```
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 , Filtered only stores with full 12 month observation.

In [15]:
```
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_o
bserv_index)]
pretrial_full_observ = full_observ[full_observ["YEARMONTH"] < 201902]

pretrial_full_observ.head(8)
```

Out[15]:

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

In [21]:
```
def calcCorrTable(metricCol, storeComparison, inputTable=pretrial_full_observ
):
    """Calculated correlation for a measure, looping through each control stor
e.
    Argument:
        metricCol (str): Name of column containing store's metric to perform c
orrelation test on.
        storeComparison (int): Trial store's number.
        inputTable (dataframe):  Metric table with potential comparison store
s.

    Returns:
        DataFrame: Monthly correlation table between Trial and each Control st
ores.
    """
    control_store_nbrs = inputTable[~inputTable["STORE_NBR"].isin([77, 86, 88
])]["STORE_NBR"].unique()
    corrs = pd.DataFrame(columns = ["YEARMONTH", "Trial_Str", "Ctrl_Str", "Cor
r_Score"])
    trial_store = inputTable[inputTable["STORE_NBR"] == storeComparison][metri
cCol].reset_index()
    for control in control_store_nbrs:
        concat_df = pd.DataFrame(columns = ["YEARMONTH", "Trial_Str", "Ctrl_St
r", "Corr_Score"])
        control_store = inputTable[inputTable["STORE_NBR"] == control][metricC
ol].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"] == st
oreComparison]["YEARMONTH"])
        corrs = pd.concat([corrs, concat_df])
    return corrs
```

In [22]:
```
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[22]:

	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 [23]:
```
def calculateMagnitudeDistance(metricCol, storeComparison, inputTable=pretrial
_full_observ):
    """Calculate standardised magnitude distance for a measure, looping throug
h each control store.
    Arguments:
        metricCol (str): Name of column containing store's metric to perform d
istance calculation on.
        storeComparison (int): Trial store's number.
        inputTable (dataframe):  Metric table with potential comparison store
s.

    Returns:
        DataFrame: Monthly magnitude-distance table between Trial and each Con
trol stores.
    """
    control_store_nbrs = inputTable[~inputTable["STORE_NBR"].isin([77, 86, 88
])]["STORE_NBR"].unique()
    dists = pd.DataFrame()
    trial_store = inputTable[inputTable["STORE_NBR"] == storeComparison][metri
cCol]
    for control in control_store_nbrs:
        concat_df  = abs(inputTable[inputTable["STORE_NBR"] == storeComparison
].reset_index()[metricCol] - inputTable[inputTable["STORE_NBR"] == control].re
set_index()[metricCol])
        concat_df["YEARMONTH"] = list(inputTable[inputTable["STORE_NBR"] == st
oreComparison]["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 [24]:
```
dist_table = pd.DataFrame()
for trial_num in [77, 86, 88]:
    dist_table = pd.concat([dist_table, calculateMagnitudeDistance(["TOT_SALE
S", "nCustomers", "nTxnPerCust", "nChipsPerTxn", "avgPricePerUnit"], trial_num
)])

dist_table.head(8)
dist_table
```

Out[24]:

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

5397 rows × 9 columns

In [25]:
```
def combine_corr_dist(metricCol, storeComparison, inputTable=pretrial_full_obs
erv):
    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 [26]:
```
compare_metrics_table1 = pd.DataFrame()
for trial_num in [77, 86, 88]:
    compare_metrics_table1 = pd.concat([compare_metrics_table1, combine_corr_d
ist(["TOT_SALES"], trial_num)])
```

In [27]:
```
corr_weight = 0.5
dist_weight = 1 - corr_weight
```

Top 5 stores with highest composite score in regards with total sales

In [28]:
```
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 [29]:
```
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)])
```

Top 5 stores with highest composite score in regards with customers

In [31]:
```
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 [32]:
```
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
```

Top 3 similarity based on TOT_SALES:

Trial store 77: Store 233, 255, 188

Trial store 86: Store 109, 155, 222

Trial store 88: Store 40, 26, 72

Top 3 similartiy based on nCustomers:

Trial store 77: Store 233, 41, 111

Trial store 86: Store 155, 225, 109

Trial store 88: Store 237, 203, 40

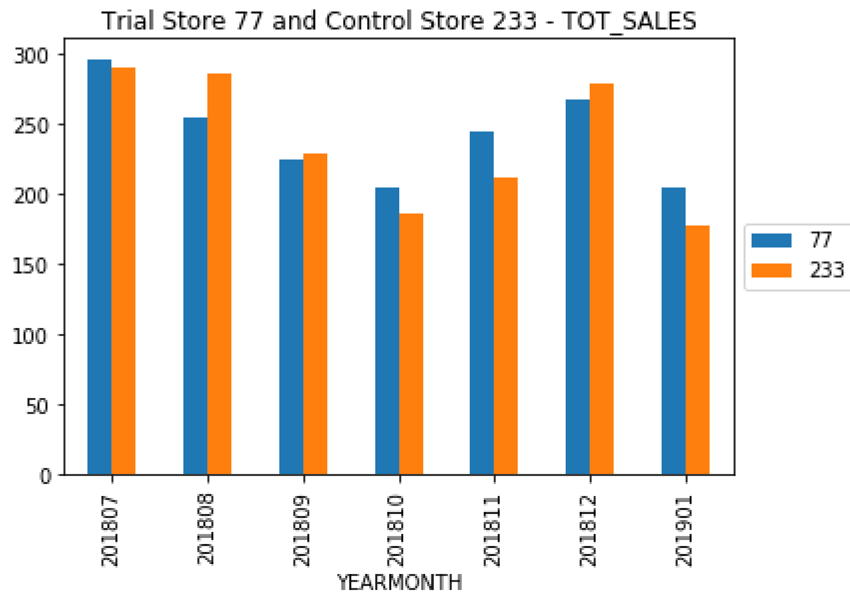
Based on highest average of both features combined:

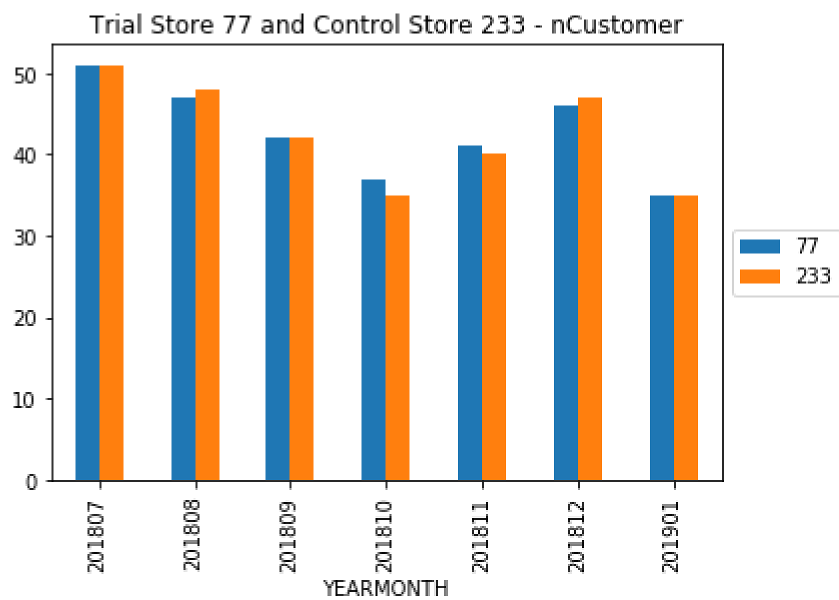
Trial store 77: Store 233

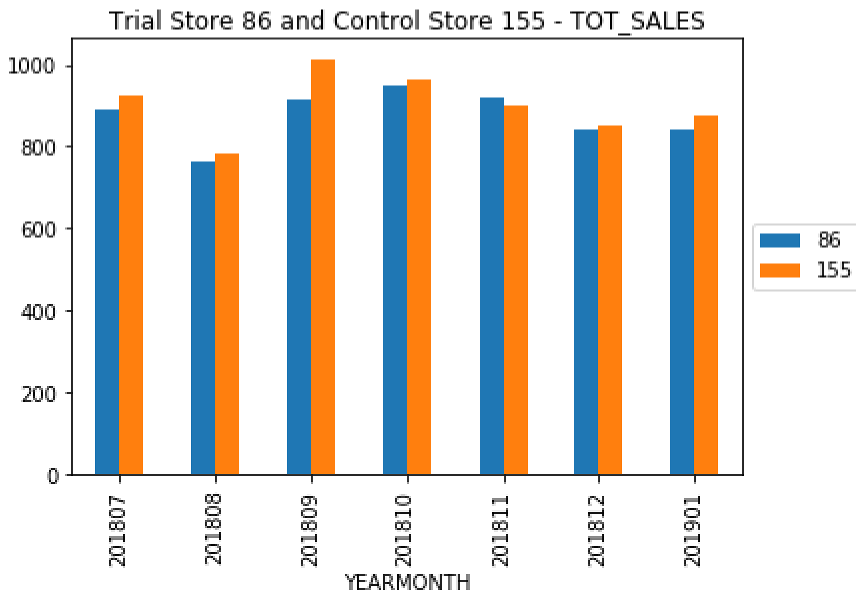
Trial store 86: Store 155

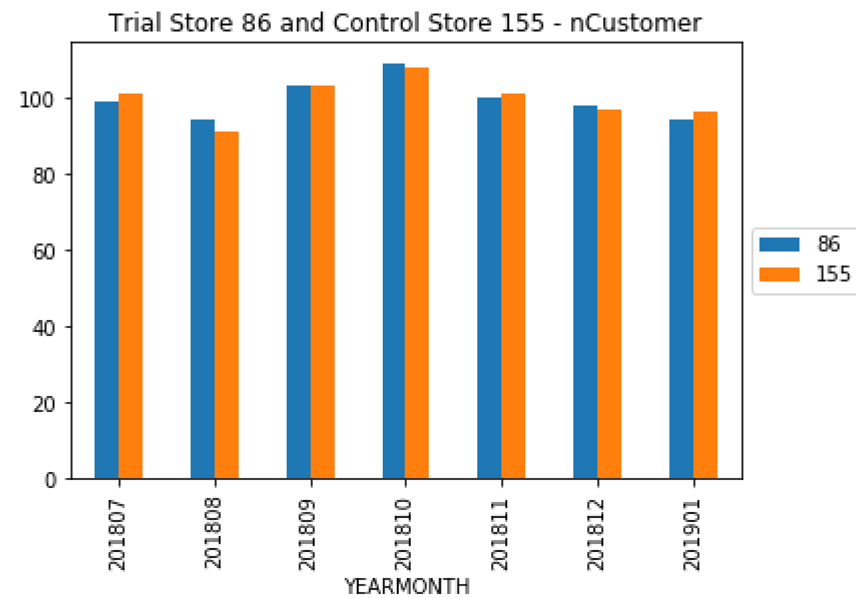
Trial store 88: Store 40

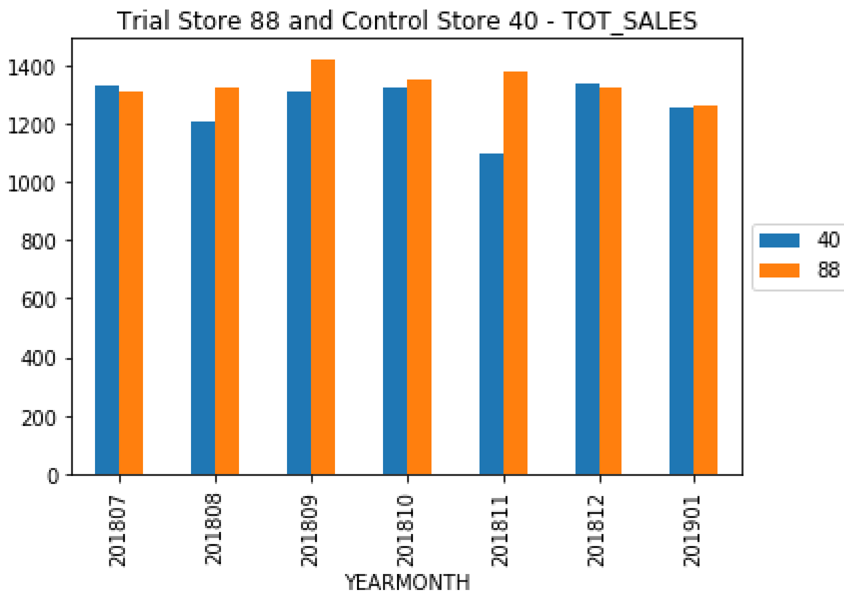
In [33]:
```
trial_control_dic = {77:233, 86:155, 88:40}
for key, val in trial_control_dic.items():
    pretrial_full_observ[pretrial_full_observ["STORE_NBR"].isin([key, val])].g
roupby(
        ["YEARMONTH", "STORE_NBR"]).sum()["TOT_SALES"].unstack().plot.bar()
    plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
    plt.title("Trial Store "+str(key)+" and Control Store "+str(val)+" - TOT_S
ALES")
    plt.show()
    pretrial_full_observ[pretrial_full_observ["STORE_NBR"].isin([key, val])].g
roupby(
    ["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)+" - nCust
omer")
    plt.show()
    print('\n')
```

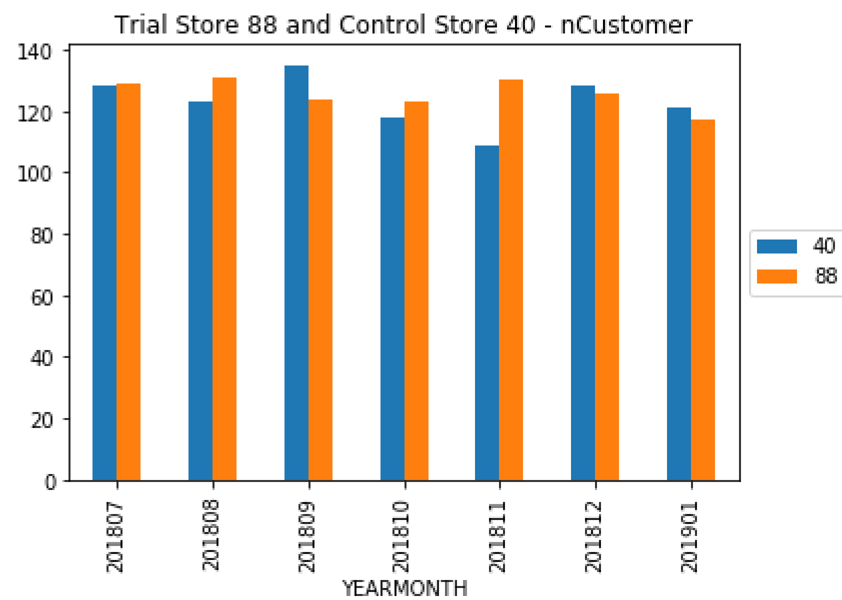

Trial Store 77 and Control Store 233 - TOT_SALES
300
250
200
150
100
50
0
201807
201808
201809
201810
201811
201812
201901
YEARMONTH
77
233


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





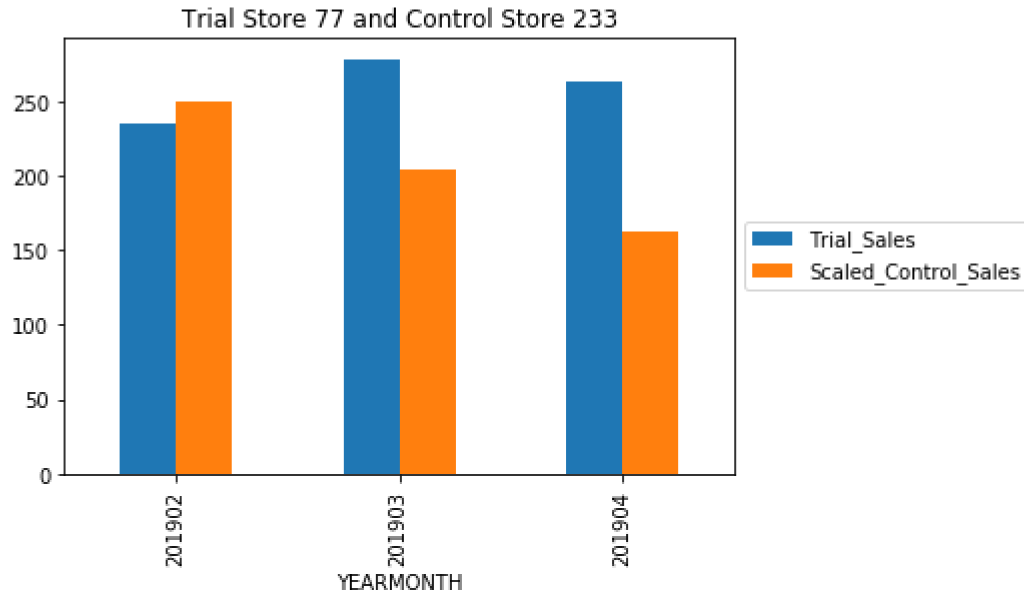
Now, we'll compare the performance of Trial stores to Control stores during the trial period. To ensure their performance is comparable during Trial period, we need to scale (multiply to ratio of trial / control) all of Control stores' performance to Trial store's performance during pre-trial. Starting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

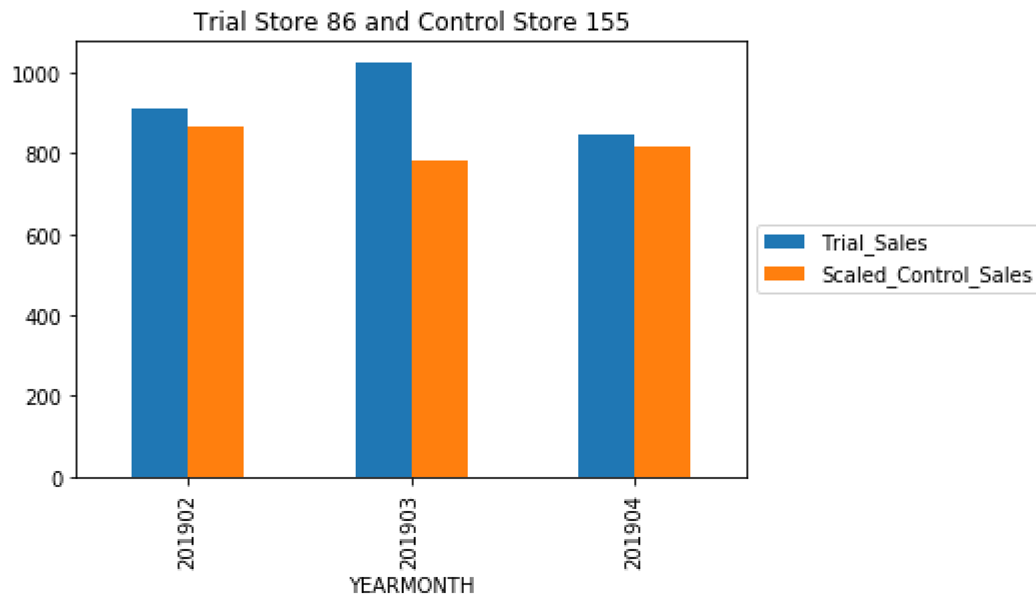
Ratio of Store 77 and its Control store.

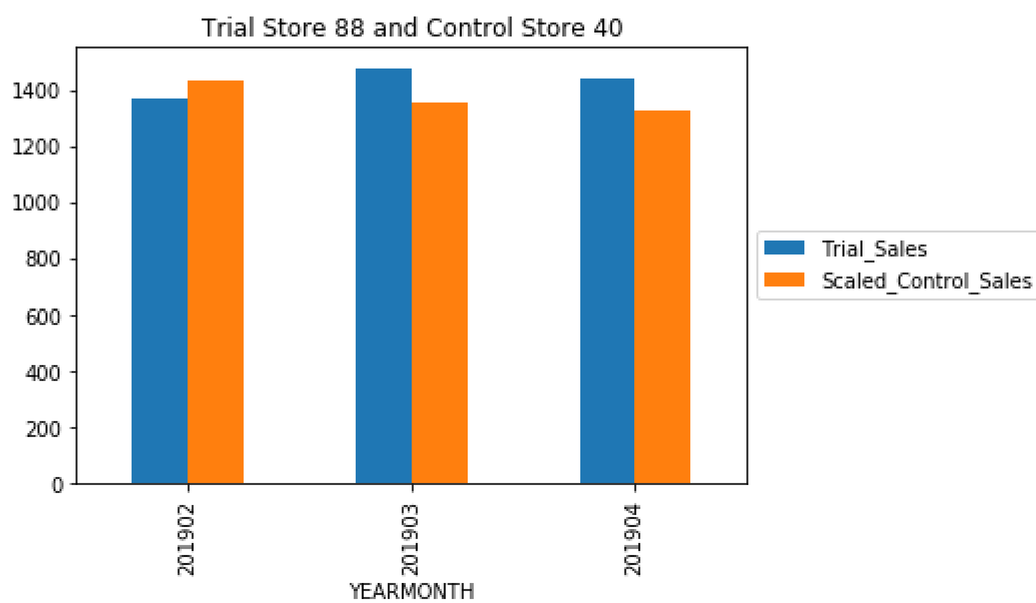
In [34]:
```
sales_ratio_77 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 77]
["TOT_SALES"].sum() / pretrial_full_observ[pretrial_full_observ["STORE_NBR"] =
= 233]["TOT_SALES"].sum()

#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 [35]:
```
trial_full_observ = full_observ[(full_observ["YEARMONTH"] >= 201902) & (full_o
bserv["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["YEARMON
TH"] <= 201904)]
pretrial_scaled_sales_control_stores = scaled_sales_control_stores[scaled_sale
s_control_stores["YEARMONTH"] < 201902]
```

In [36]:
```
percentage_diff = {}

for trial, control in trial_control_dic.items():
    a = trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["S
TORE_NBR"] == control]
    b = trial_full_observ[trial_full_observ["STORE_NBR"] == trial][["STORE_NB
R", "YEARMONTH", "TOT_SALES"]]
    percentage_diff[trial] = b["TOT_SALES"].sum() / a["ScaledSales"].sum()
    b[["YEARMONTH", "TOT_SALES"]].merge(a[["YEARMONTH", "ScaledSales"]],on="YE
ARMONTH").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
0
50
100
150
200
250
201902
201903
201904
YEARMONTH
Trial_Sales
Scaled_Control_Sales


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


Trial Store 88 and Control Store 40
0
200
400
600
800
1000
1200
1400
201902
201903
201904
YEARMONTH
Trial_Sales
Scaled_Control_Sales

In [37]:
```
percentage_diff
```

Out[37]: {77: 1.2615468650086274, 86: 1.13150143573637, 88: 1.0434583458542188}

Compiled percetage difference table

In [38]:
```
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_S
ALES"] - scaledsales_vs_trial["c_ScaledSales"]) / (((scaledsales_vs_trial["t_T
OT_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[38]:

	c_STORE_NBR	YEARMONTH	c_ScaledSales	t_STORE_NBR	t_TOT_SALES	Sales_Percentag
7	233	201902	249.762622	77	235.0	-0.0
8	233	201903	203.802205	77	278.5	0.3
9	233	201904	162.345704	77	263.5	0.4
19	155	201902	864.522060	86	913.2	0.0
20	155	201903	780.320405	86	1026.8	0.2
21	155	201904	819.317024	86	848.2	0.0
31	40	201902	1434.399269	88	1370.2	-0.0
32	40	201903	1352.064709	88	1477.2	0.0
33	40	201904	1321.797762	88	1439.4	0.0

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 [40]:
```
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"] == num]["ScaledSales"],
                   trial_scaled_sales_control_stores[trial_scaled_sales_contro
l_stores["STORE_NBR"] == num]["ScaledSales"],
                   equal_var=False), '\n')
    #print(len(pretrial_scaled_sales_control_stores[pretrial_scaled_sales_cont
rol_stores["STORE_NBR"] == num]["ScaledSales"]), len(trial_scaled_sales_contro
l_stores[trial_scaled_sales_control_stores["STORE_NBR"] == num]["ScaledSale
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_st
ores[pretrial_scaled_sales_control_stores["STORE_NBR"] == num]),
                       len(trial_scaled_sales_control_stores[trial_scaled_sale
s_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 [41]:
```
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 no statistically difference between control store's scaled Pre-Trial and Trial period sales.

In [42]:
```
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"] == tria
l]["TOT_SALES"]),len(pretrial_scaled_sales_control_stores[pretrial_scaled_sale
s_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_ob
serv["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 no statistically difference between Trial store's sales and Control store's scaled-sales performance during pre-trial.

In [43]:
```
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"] == co
nt) & (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_mo
nth) & (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)
```

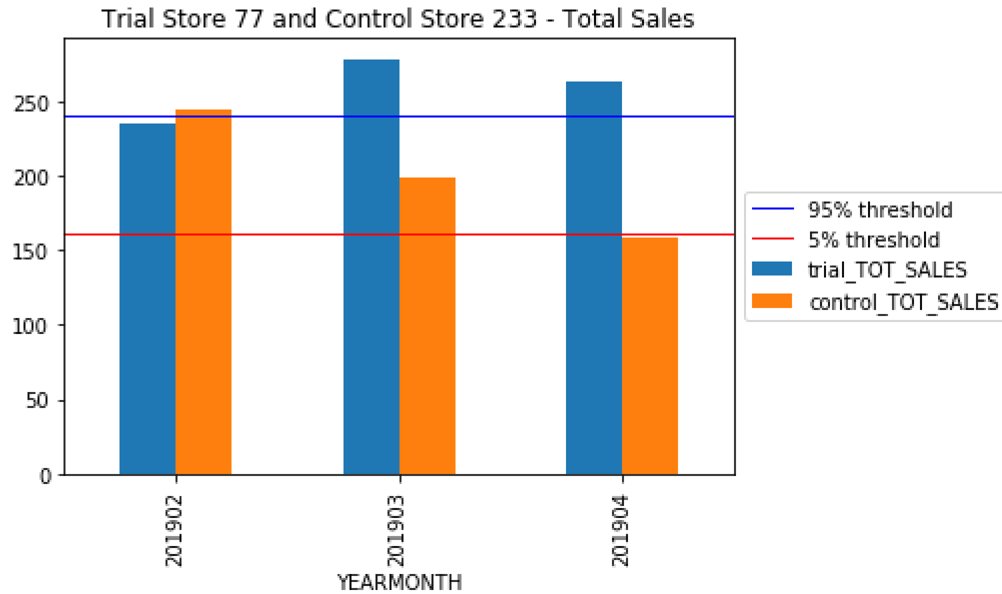
```
Trial store: 77 , Control store: 233
201902 : -0.7171038288055888
201903 : 3.035317928855662
201904 : 4.708944418758203


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
```

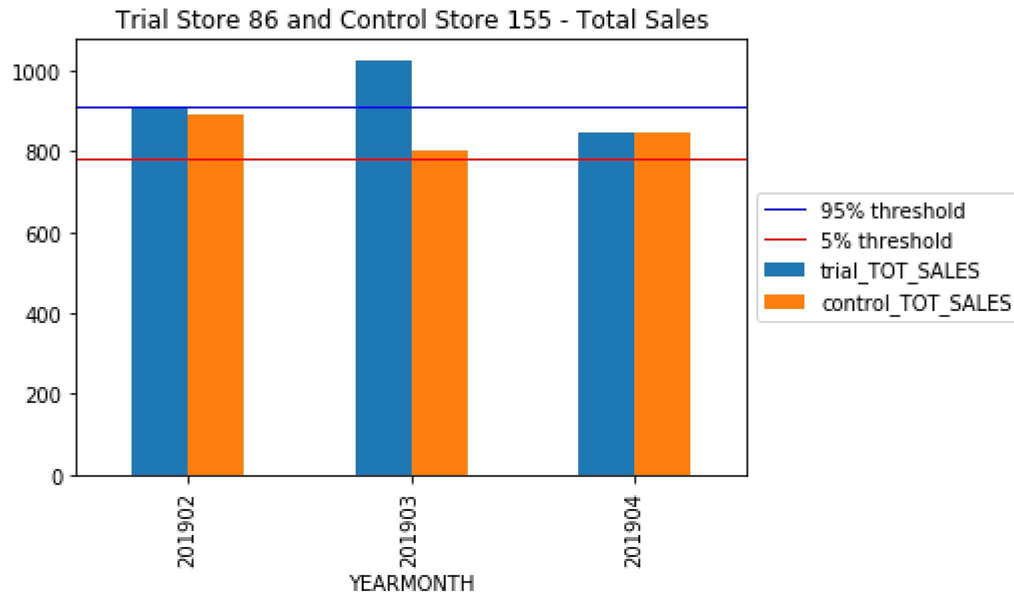
Critical t-value for 95% confidence interval:

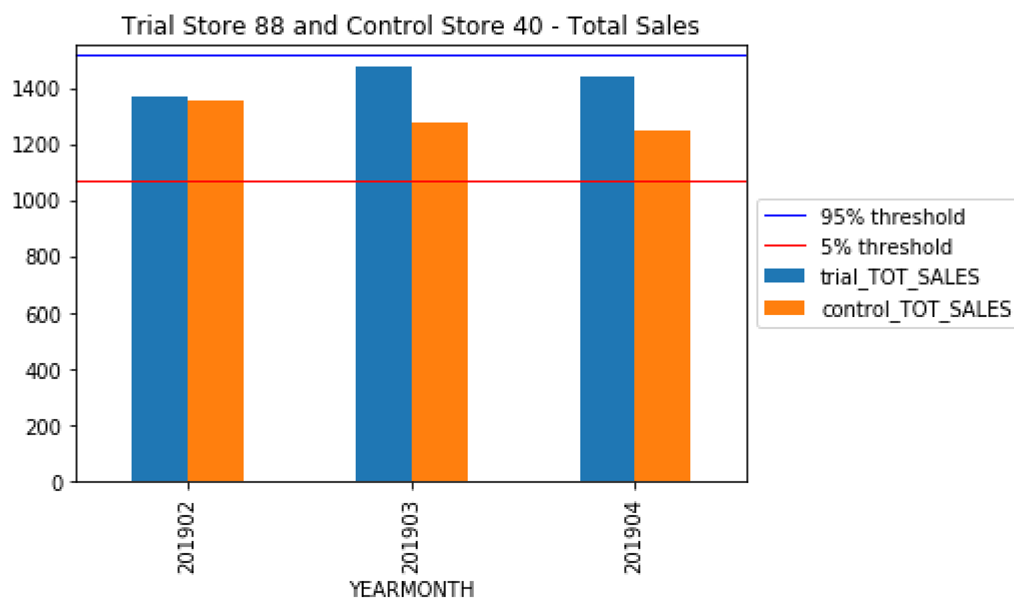
1.9431802803927816 There are 3 months' increase in performance that are statistically significant (Above the 95% confidence interval t-score):

March and April trial months for trial store 77 March trial months for trial store 86

In [44]:
```
for trial, control in trial_control_dic.items():
    a = trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["S
TORE_NBR"] == control].rename(columns={"TOT_SALES": "control_TOT_SALES"})
    b = trial_full_observ[trial_full_observ["STORE_NBR"] == trial][["STORE_NB
R", "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_contr
ol_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"].st
d()
    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 77 and Control Store 233 - Total Sales
250
200
150
100
50
0
201902
201903
201904
YEARMONTH
95% threshold
5% threshold
trial_TOT_SALES
control_TOT_SALES


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

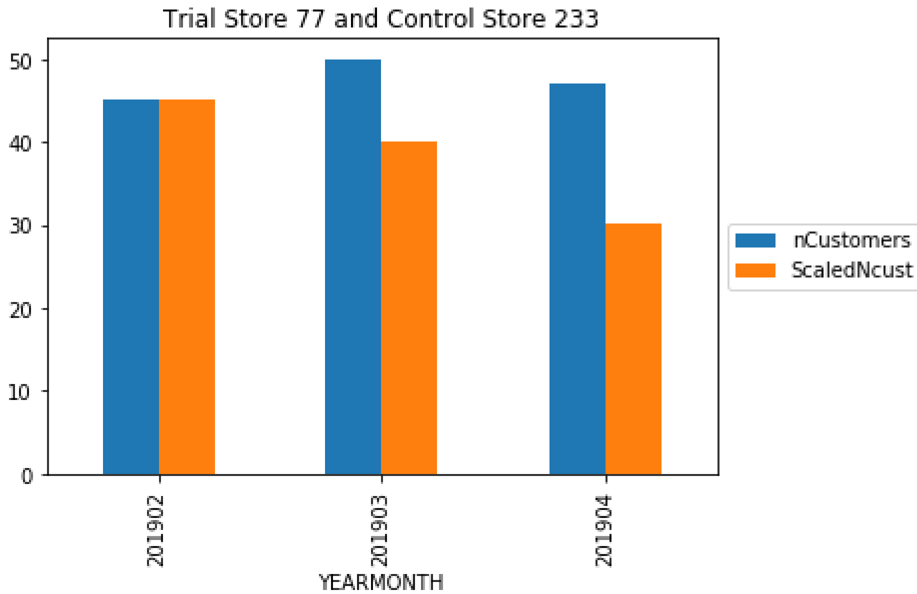
Ratio of store 77 and its control store

In [45]:
```
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()
```

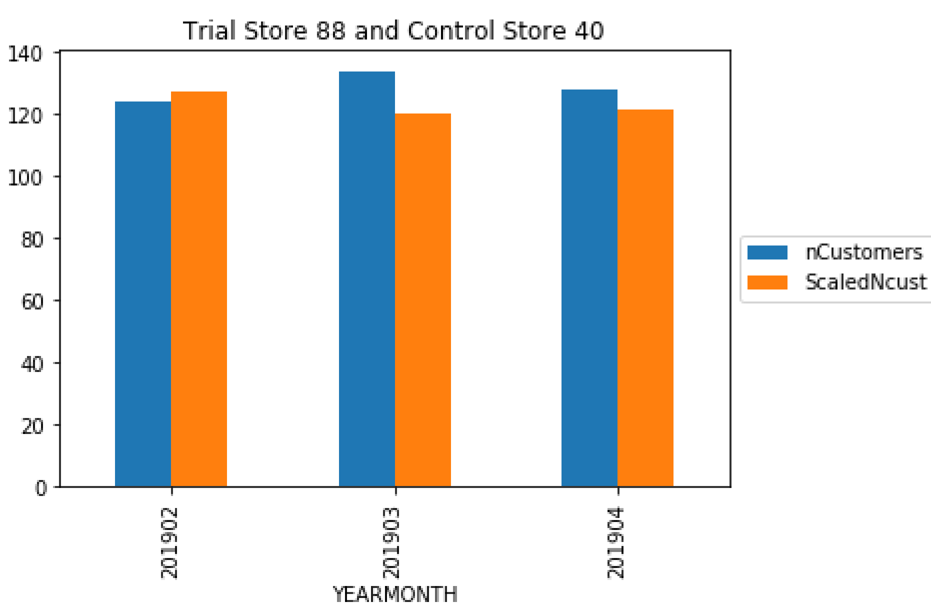
trial_full_observ = full_observ[(full_observ["YEARMONTH"] >= 201902) & (full_observ["YEARMONTH"] <= 201904)]

In [46]:
```
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["YEARMON
TH"] <= 201904)]
pretrial_scaled_ncust_control_stores = scaled_ncust_control_stores[scaled_ncus
t_control_stores["YEARMONTH"] < 201902]
```

In [47]:
```
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 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


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

In [48]:
```
ncust_percentage_diff
```

Out[48]: {77: 1.2306529009742622, 86: 1.1354166666666667, 88: 1.0444876946258161}

Created a compiled ncustpercentage difference table

In [49]:
```
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[49]:

	c_STORE_NBR	YEARMONTH	c_ScaledNcust	t_STORE_NBR	t_nCustomers	nCust_Percenta
7	233	201902	45.151007	77	45	-0.(
8	233	201903	40.134228	77	50	0.:
9	233	201904	30.100671	77	47	0.4
19	155	201902	95.000000	86	107	0.
20	155	201903	94.000000	86	115	0.:
21	155	201904	99.000000	86	105	0.(
31	40	201902	127.610209	88	124	-0.(
32	40	201903	120.464037	88	134	0.
33	40	201904	121.484919	88	128	0.(

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 [51]:
```
# 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_contro
l_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_st
ores[pretrial_scaled_ncust_control_stores["STORE_NBR"] == num]),
                       len(trial_scaled_ncust_control_stores[trial_scaled_ncus
t_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 [52]:
```
# 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_ob
serv["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 [53]:
```
# 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"] == co
nt) & (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_mo
nth) & (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)
```

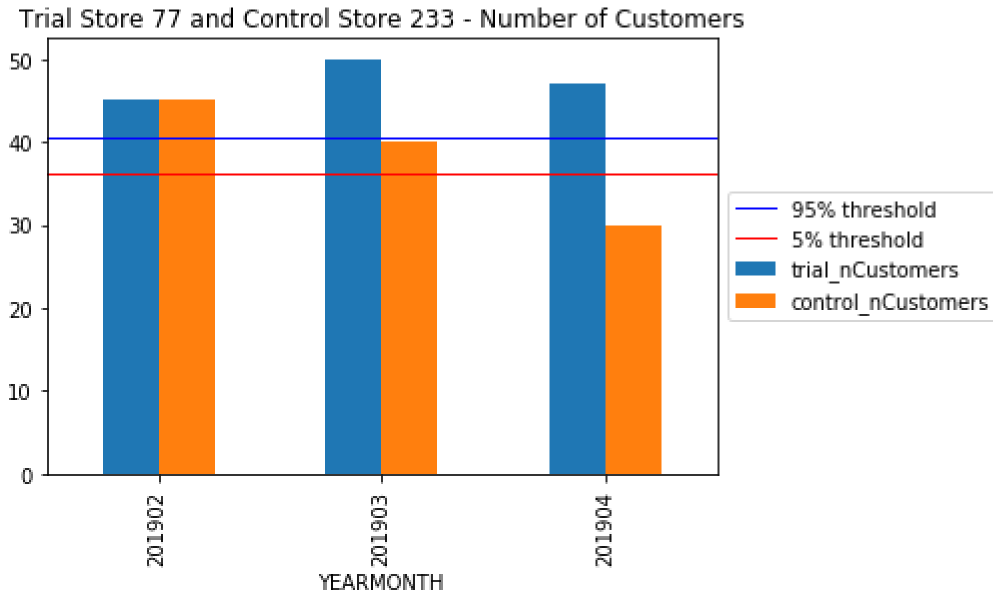
```
Trial store: 77 , Control store: 233
201902 : -0.19886295797440687
201903 : 8.009609025380932
201904 : 16.114474772873923


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
```

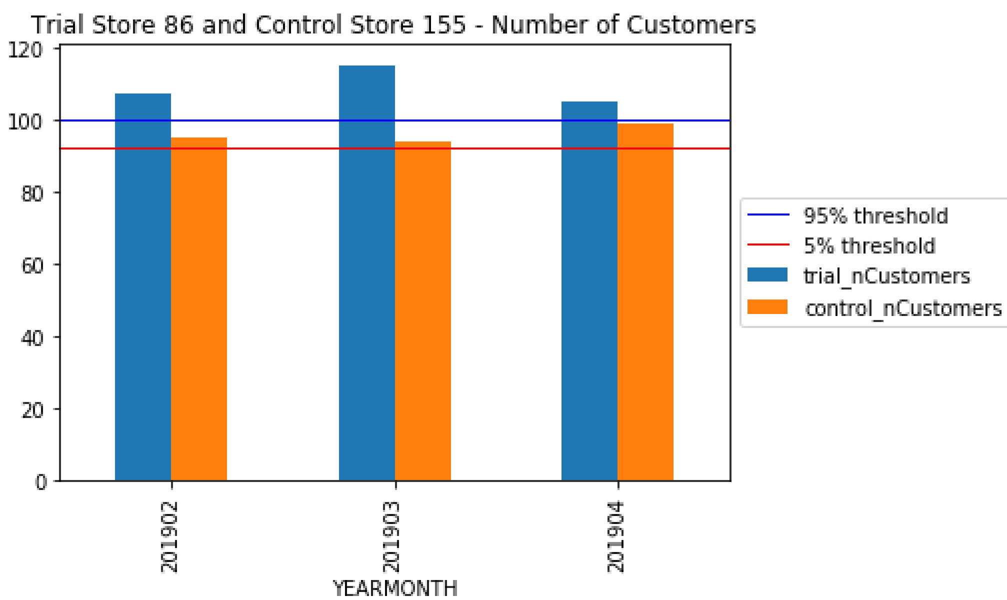
Critical t-value for 95% confidence interval:

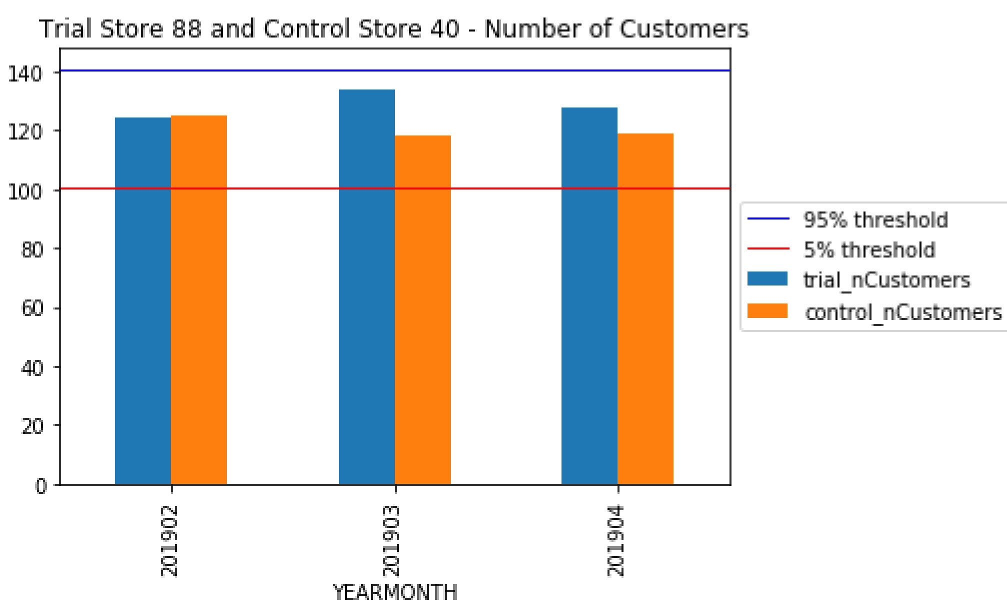
1.9431802803927816 There are 5 months' increase in performance that are statistically significant (Above the 95% confidence interval t-score):

March and April trial months for trial store 77 Feb, March and April trial months for trial store 86

In [54]:
```
for trial, control in trial_control_dic.items():
    a = trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["S
TORE_NBR"] == control].rename(columns={"nCustomers": "control_nCustomers"})
    b = trial_full_observ[trial_full_observ["STORE_NBR"] == trial][["STORE_NB
R", "YEARMONTH", "nCustomers"]].rename(columns={"nCustomers": "trial_nCustomer
s"})
    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_contr
ol_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"].st
d()
    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")
```


Trial Store 77 and Control Store 233 - Number of Customers
50
40
30
20
10
0
201902
201903
201904
YEARMONTH
95% threshold
5% threshold
trial_nCustomers
control_nCustomers


Trial Store 86 and Control Store 155 - Number of Customers
120
100
80
60
40
20
0
201902
201903
201904
YEARMONTH
95% threshold
5% threshold
trial_nCustomers
control_nCustomers


Trial Store 88 and Control Store 40 - Number of Customers
140
120
100
80
60
40
20
0
201902
201903
201904
YEARMONTH
95% threshold
5% threshold
trial_nCustomers
control_nCustomers

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.

In [ ]:

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