Quantium - Module 2

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

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

```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
```

```
qvi = pd.read_csv("QVI_data.csv")
qvi.head()
```

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

```
# Checking for nulls
qvi.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264834 entries, 0 to 264833
Data columns (total 12 columns):
LYLTY_CARD_NBR      264834 non-null int64
DATE                264834 non-null object
STORE_NBR           264834 non-null int64
TXN_ID              264834 non-null int64
PROD_NBR            264834 non-null int64
PROD_NAME           264834 non-null object
PROD_QTY            264834 non-null int64
TOT_SALES           264834 non-null float64
PACK_SIZE           264834 non-null int64
BRAND               264834 non-null object
LIFESTAGE           264834 non-null object
PREMIUM_CUSTOMER    264834 non-null object
dtypes: float64(1), int64(6), object(5)
memory usage: 24.2+ MB
```

- Client has selected store numbers 77, 86 and 88 as trial stores.
- Client wants control stores to be established stores that are operational for the entire observation period.
- Trial period = 1 Feb 2019 to 30 April 2019.
- Compare trial stores to control stores that are similar pre-trial. Similarity measurement:
  - Monthly overall sales revenue
  - Monthly number of customers
  - Monthly number of transactions per customer

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

Compile each store's monthly

Compile each store's monthly:

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

```
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
```

```
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):
STORE_NBR          3169 non-null int64
YEARMONTH          3169 non-null int64
TOT_SALES          3169 non-null float64
nCustomers         3169 non-null int64
nTxnPerCust        3169 non-null float64
nChipsPerTxn       3169 non-null float64
avgPricePerUnit    3169 non-null float64
dtypes: float64(4), int64(3)
memory usage: 173.4 KB
```

```
#pre trial observation
#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)
```

	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

```
def calcCorrTable(metricCol, storeComparison, inputTable=pretrial_full_observ):
    """Calculate correlation for a measure, looping through each control store.
    Args:
        metricCol (str): Name of column containing store's metric to perform correlation test on.
        storeComparison (int): Trial store's number.
        inputTable (dataframe):  Metric table with potential comparison stores.

    Returns:
        DataFrame: Monthly correlation table between Trial and each Control stores.
    """
    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


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_nu

corr_table.head(8)
```

	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

```
def calculateMagnitudeDistance(metricCol, storeComparison, inputTable=pretrial_full_observ):
    """Calculate standardised magnitude distance for a measure, looping through each control store.
    Args:
        metricCol (str): Name of column containing store's metric to perform distance calculation on.
        storeComparison (int): Trial store's number.
        inputTable (dataframe):  Metric table with potential comparison stores.

    Returns:
        DataFrame: Monthly magnitude-distance table between Trial and each Control 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][metricCol]
    for control in control_store_nbrs:
        concat_df  = abs(inputTable[inputTable["STORE_NBR"] == storeComparison].reset_index()[metricCol] - inputTable[inputTable["STORE_NBR"]
        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


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

dist_table.head(8)
dist_table
```

	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
5	0.944193	0.961538	0.868716	0.857966	0.770744	201812	77	1	0.880632
6	0.964375	1.000000	0.790956	0.551428	0.678728	201901	77	1	0.797098
0	0.895138	0.884615	0.933787	0.680831	0.848622	201807	77	2	0.848599
1	0.955685	0.923077	0.801752	0.887907	0.957997	201808	77	2	0.905284
2	0.949149	0.942308	0.951610	0.639734	0.674207	201809	77	2	0.831401
3	0.973641	0.961538	0.946947	0.789862	0.879075	201810	77	2	0.910213
4	0.940817	0.980769	0.884082	0.654639	0.975730	201811	77	2	0.887208
5	0.905696	0.894231	0.950011	0.711693	0.814511	201812	77	2	0.855228
6	0.970121	0.923077	0.834709	0.510153	0.894500	201901	77	2	0.826512
0	0.347195	0.413462	0.625121	0.472626	0.456197	201807	77	3	0.462920
1	0.407994	0.375000	0.572831	0.532780	0.515987	201808	77	3	0.480919
2	0.428069	0.423077	0.709661	0.585080	0.295745	201809	77	3	0.488326
3	0.401422	0.355769	0.714158	0.416908	0.712701	201810	77	3	0.520192
4	0.452201	0.423077	0.767953	0.581302	0.537221	201811	77	3	0.552351
5	0.386411	0.375000	0.763567	0.500275	0.592701	201812	77	3	0.523591
6	0.391439	0.355769	0.824430	0.688332	0.220983	201901	77	3	0.496191
0	0.207714	0.259615	0.581571	0.428439	0.484040	201807	77	4	0.392276
1	0.278891	0.269231	0.496706	0.465342	0.471250	201808	77	4	0.396284
2	0.300869	0.259615	0.726740	0.554487	0.331541	201809	77	4	0.434650
3	0.179846	0.173077	0.431418	0.238944	0.756281	201810	77	4	0.355914
4	0.305681	0.259615	0.744420	0.507302	0.585225	201811	77	4	0.480449
5	0.340444	0.442308	0.478993	0.322527	0.557828	201812	77	4	0.428420
6	0.051408	0.048077	0.659014	0.561179	0.164031	201901	77	4	0.206040

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.

```
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


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)])


corr_weight = 0.5
dist_weight = 1 - corr_weight


#Top 5 highest Composite Score for each Trial Store based on TOT_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["
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(),
```

```
     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
```

```
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 highest Composite Score for each Trial Store based on nCustomers
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["
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(),
```

```
     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
```

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

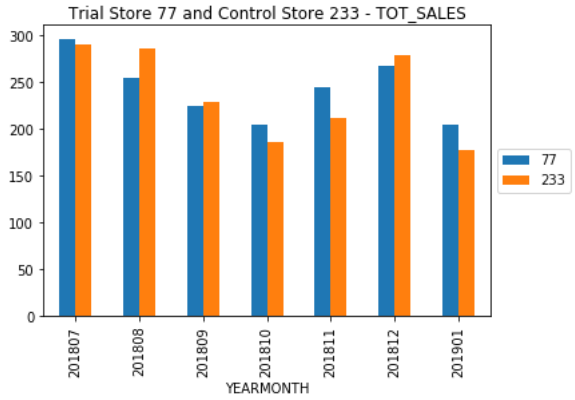
Top 3 similartiy based on nCustomers:

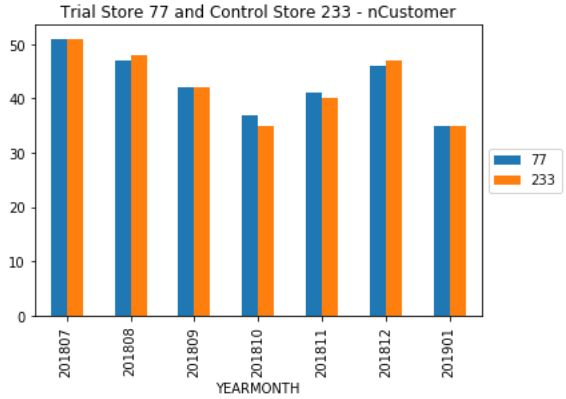
- Trial store 77: Store 233, 41, 111
- Trial store 86: Store 155, 225, 109
- Trial store 88: Store 237, 203, 40

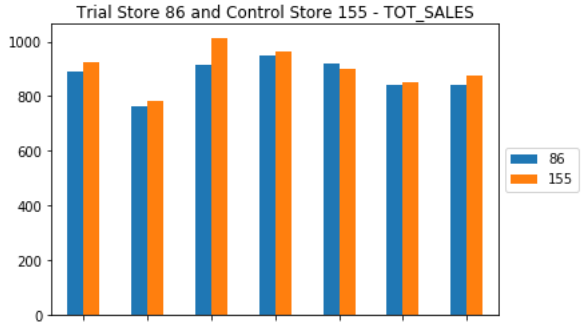
Based on highest average of both features combined:

- Trial store 77: Store 233
- Trial store 86: Store 155
- Trial store 88: Store 40

```
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')
```

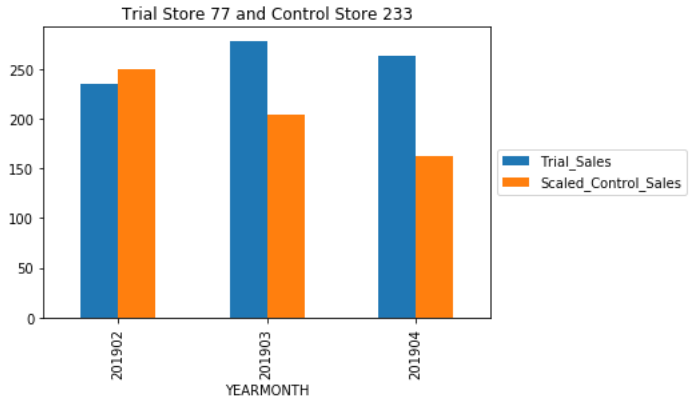

Trial Store 77 and Control Store 233 - TOT_SALES
300
250
200
150
100
50
0
201807
201808
201809
201810
201811
201812
201901
YEARMONTH
77
233

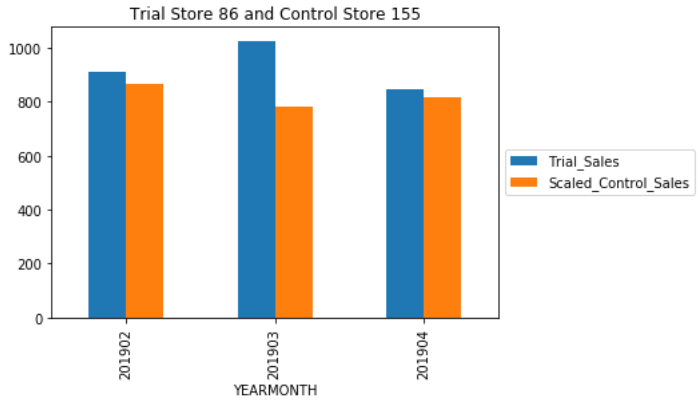

Trial Store 77 and Control Store 233 - nCustomer
50
40
30
20
10
0
201807
201808
201809
201810
201811
201812
201901
YEARMONTH
77
233


Trial Store 86 and Control Store 155 - TOT_SALES
1000
800
600
400
200
0
86
155

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.

```
#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

#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

#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



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_s
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":
    plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
    plt.title("Trial Store "+str(trial)+" and Control Store "+str(control))
```






```
percentage_diff
```

```
{77: 1.2615468650086274, 86: 1.13150143573637, 88: 1.0434583458542188}
```

```
#Creating a compiled percentage_difference table
temp1 = scaled_sales_control_stores.sort_values(by=["STORE_NBR", "YEARMONTH"], ascending=[False, True]).reset_index().drop(["TOT_SALES", "ind
temp2 = full_observ[full_observ["STORE_NBR"].isin([77,86,88])][["STORE_NBR", "YEARMONTH", "TOT_SALES"]].reset_index().drop(["index", "YEARMON
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"]) / (((scaledsale
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"]
```

	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

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)

```
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_control_stores["STORE_NBR"] == num]["ScaledSales"],
                    equal_var=False), '\n')
    #print(len(pretrial_scaled_sales_control_stores[pretrial_scaled_sales_control_stores["STORE_NBR"] == num]["ScaledSales"]), len(trial_scale

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

```
Store 40
Ttest_indResult(statistic=-0.5958372343168585, pvalue=0.5722861621434009)

Store 155
Ttest_indResult(statistic=1.429195687929098, pvalue=0.19727058651603258)

Store 233
Ttest_indResult(statistic=1.1911026010974504, pvalue=0.29445006064862156)

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

```
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.

```
# 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[pretri

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

```
Trial store: 77 , Control store: 233
Ttest_indResult(statistic=-1.2533353315065926e-15, pvalue=0.999999999999999)

Trial store: 86 , Control store: 155
Ttest_indResult(statistic=0.0, pvalue=1.0)

Trial store: 88 , Control store: 40
Ttest_indResult(statistic=0.0, pvalue=1.0)

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

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

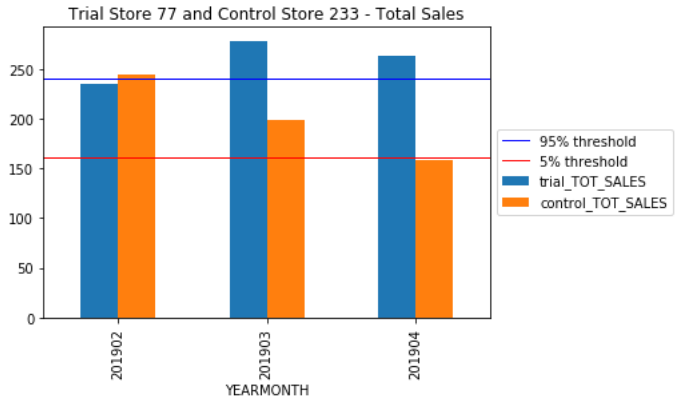
```
# Step 3
for trial, cont in trial_control_dic.items():
    print("Trial store:", trial, ", Control store:", cont)
    temp_pre = scaledsales_vs_trial[(scaledsales_vs_trial["c_STORE_NBR"] == cont) & (scaledsales_vs_trial["trial_period"]=="pre")]
    std = temp_pre["Sales_Percentage_Diff"].std()
    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_P
        print(t_month,":",(float(pdif)-mean)/std)
    print('\n')

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

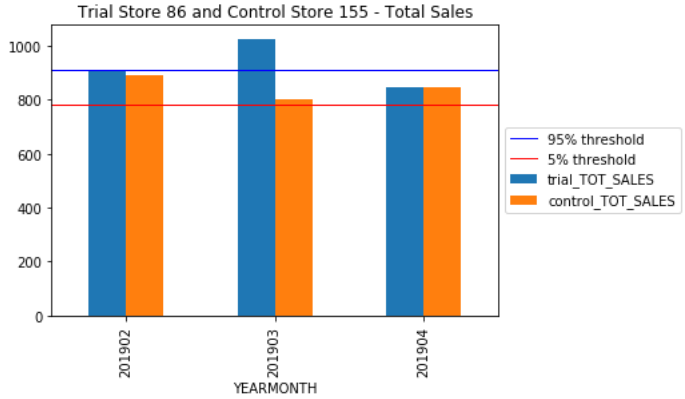
```
 Trial store: 77 , Control store: 233
 201902 : -0.7171038288055888
 201903 : 3.035317928855662
 201904 : 4.708944418758203


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


 Trial store: 88 , Control store: 40
 201902 : -0.5481633746817604
 201903 : 1.0089992743637755
 201904 : 0.9710006270463645


 Critical t-value for 95% confidence interval:
 1.9431802803927816
```

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

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

```
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_TO
    b = trial_full_observ[trial_full_observ["STORE_NBR"] == trial][["STORE_NBR", "YEARMONTH", "TOT_SALES"]].rename(columns={"TOT_SALES": "tri
    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_Perce
    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")
```



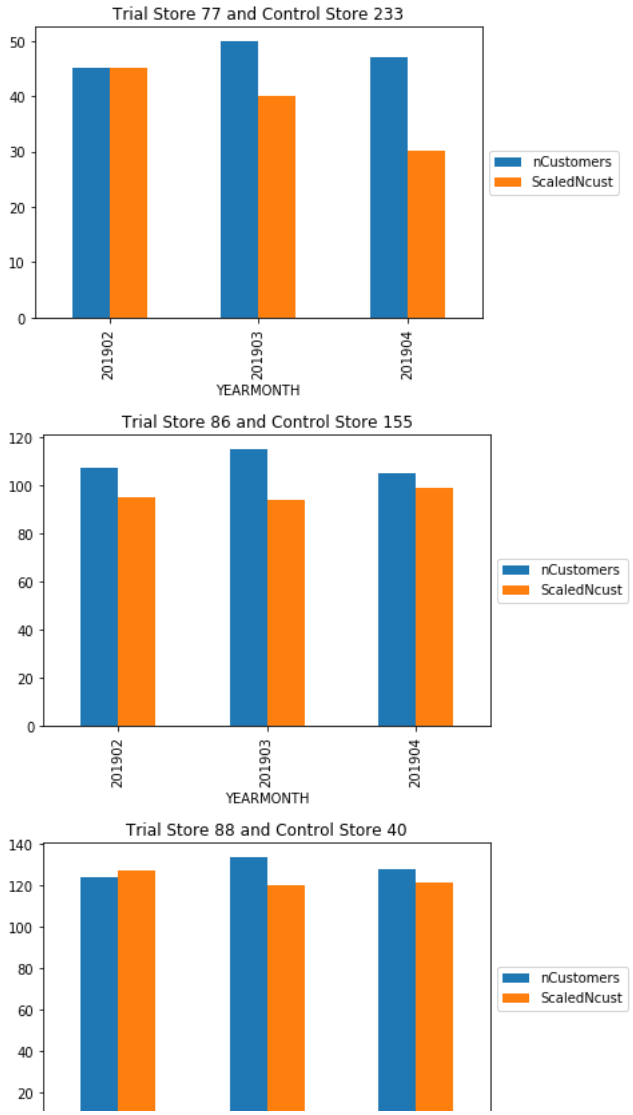


Trial Store 88 and Control Store 40 - Total Sales

We can see that Trial store 77 sales for March and April exceeds 95% threshold of control store. Same goes to store 86 sales for March.

Next, we'll look into nCustomers.


```
#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_obser

#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_obser

#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_obser



#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_
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"
    plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
    plt.title("Trial Store "+str(trial)+" and Control Store "+str(control))
```




```
ncust_percentage_diff
```

```
{77: 1.2306529009742622, 86: 1.1354166666666667, 88: 1.0444876946258161}
```

```
#Creating a compiled ncust_percentage_difference table
temp1 = scaled_ncust_control_stores.sort_values(by=["STORE_NBR", "YEARMONTH"], ascending=[False, True]).reset_index().drop(["nCustomers", "in
temp2 = full_observ[full_observ["STORE_NBR"].isin([77,86,88])][["STORE_NBR", "YEARMONTH", "nCustomers"]].reset_index().drop(["index", "YEARMO
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"]) / (((scaledncu

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

	c_STORE_NBR	YEARMONTH	c_ScaledNcust	t_STORE_NBR	t_nCustomers	nCust_Percentage_D
7	233	201902	45.151007	77	45	-0.003
8	233	201903	40.134228	77	50	0.218

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.

```
# Step 1
for num in [40, 155, 233]:
    print("Store", num)
    print(ttest_ind(pretrial_scaled_ncust_control_stores[pretrial_scaled_ncust_control_stores["STORE_NBR"] == num]["ScaledNcust"],
                    trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["STORE_NBR"] == num]["ScaledNcust"],
                    equal_var=False), '\n')

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

```
Store 40
Ttest_indResult(statistic=0.644732693420032, pvalue=0.5376573016017127)

Store 155
Ttest_indResult(statistic=1.3888888888888882, pvalue=0.204345986327886)

Store 233
Ttest_indResult(statistic=0.8442563765225701, pvalue=0.4559280037660254)

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

```
# Step 2
for trial, cont in trial_control_dic.items():
    print("Trial store:", trial, ", Control store:", cont)
    print(ttest_ind(pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == trial]["nCustomers"],
                    pretrial_scaled_ncust_control_stores[pretrial_scaled_ncust_control_stores["STORE_NBR"] == cont]["ScaledNcust"],
                    equal_var=True), '\n')

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

```
Trial store: 77 , Control store: 233
Ttest_indResult(statistic=0.0, pvalue=1.0)

Trial store: 86 , Control store: 155
Ttest_indResult(statistic=0.0, pvalue=1.0)

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

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

```
# 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_P
        print(t_month,":",(float(pdif)-mean)/std)
    print('\n')

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

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


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


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


Critical t-value for 95% confidence interval:
1.9431802803927816
```

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

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

```
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_n
    b = trial_full_observ[trial_full_observ["STORE_NBR"] == trial][["STORE_NBR", "YEARMONTH", "nCustomers"]].rename(columns={"nCustomers": "t
    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_Perce
    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")
```