qvi-task2

May 8, 2024

1 Quantium Virtual Internship - Retail Strategy and Analytics - Task 2

[1]:
```
# Loading required libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import datetime
from scipy import stats
```

[2]:
```
# Read data files into data frames
df = pd.read_csv('QVI_data.csv')
df
```

[2]:
```
        LYLTY_CARD_NBR        DATE  STORE_NBR  TXN_ID  PROD_NBR  \
0                 1000  2018-10-17          1       1         5
1                 1002  2018-09-16          1       2        58
2                 1003  2019-03-07          1       3        52
3                 1003  2019-03-08          1       4       106
4                 1004  2018-11-02          1       5        96
…                    …           …        …       …         …
264829         2370701  2018-12-08         88  240378        24
264830         2370751  2018-10-01         88  240394        60
264831         2370961  2018-10-24         88  240480        70
264832         2370961  2018-10-27         88  240481        65
264833         2373711  2018-12-14         88  241815        16

                                       PROD_NAME  PROD_QTY  TOT_SALES  \
0         Natural Chip        Compny SeaSalt175g         2        6.0
1          Red Rock Deli Chikn&Garlic Aioli 150g         1        2.7
2          Grain Waves Sour    Cream&Chives 210G         1        3.6
3         Natural ChipCo      Hony Soy Chckn175g         1        3.0
4                 WW Original Stacked Chips 160g         1        1.9
…                                            …         …          …
264829     Grain Waves         Sweet Chilli 210g         2        7.2
264830      Kettle Tortilla ChpsFeta&Garlic 150g         2        9.2
264831   Tyrrells Crisps     Lightly Salted 165g         2        8.4
```

```
264832  Old El Paso Salsa   Dip Chnky Tom Ht300g        2       10.2
264833  Smiths Crinkle Chips Salt & Vinegar 330g        2       11.4

        PACK_SIZE       BRAND              LIFESTAGE PREMIUM_CUSTOMER
0             175     NATURAL  YOUNG SINGLES/COUPLES          Premium
1             150         RRD  YOUNG SINGLES/COUPLES       Mainstream
2             210     GRNWVES         YOUNG FAMILIES           Budget
3             175     NATURAL         YOUNG FAMILIES           Budget
4             160  WOOLWORTHS  OLDER SINGLES/COUPLES       Mainstream
…           …         …                    …              …
264829        210     GRNWVES         YOUNG FAMILIES       Mainstream
264830        150      KETTLE         YOUNG FAMILIES          Premium
264831        165    TYRRELLS         OLDER FAMILIES           Budget
264832        300         OLD         OLDER FAMILIES           Budget
264833        330      SMITHS  YOUNG SINGLES/COUPLES       Mainstream

[264834 rows x 12 columns]
```

The client has selected store numbers 77, 86 and 88 as trial stores with a trial period of Feb 2019 to April 2019. The client also wants control stores to be established stores that are operational for the entire observation period.

We would want to match trial stores to control stores that are similar to the trial store prior to the trial period of Feb 2019 in terms of: - Monthly overall sales revenue - Monthly number of customers - Monthly number of transactions per customer

To choose the control stores, we will create the metrics of interest and filter to stores that are present throughout the pre-trial period.

First, we want to add a column with the year/month of the transaction.

[3]:
```
# Change DATE column to store dates as datetimes
df['DATE'] = pd.to_datetime(df['DATE'])

# Then add a YEARMONTH column
df['YEARMONTH'] = df['DATE'].dt.strftime('%Y%m').astype('int64')
df
```

[3]:
```
        LYLTY_CARD_NBR       DATE  STORE_NBR  TXN_ID  PROD_NBR  \
0                 1000 2018-10-17          1       1         5
1                 1002 2018-09-16          1       2        58
2                 1003 2019-03-07          1       3        52
3                 1003 2019-03-08          1       4       106
4                 1004 2018-11-02          1       5        96
…                 …          …         …       …       …
264829         2370701 2018-12-08         88  240378        24
264830         2370751 2018-10-01         88  240394        60
264831         2370961 2018-10-24         88  240480        70
264832         2370961 2018-10-27         88  240481        65
```

```
264833        2373711 2018-12-14        88  241815        16

                                       PROD_NAME  PROD_QTY  TOT_SALES  \
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3         Natural ChipCo      Hony Soy Chckn175g         1        3.0
4                 WW Original Stacked Chips 160g         1        1.9
…                                            …       …         …
264829     Grain Waves         Sweet Chilli 210g         2        7.2
264830      Kettle Tortilla ChpsFeta&Garlic 150g         2        9.2
264831   Tyrrells Crisps     Lightly Salted 165g         2        8.4
264832  Old El Paso Salsa   Dip Chnky Tom Ht300g         2       10.2
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        PACK_SIZE       BRAND              LIFESTAGE PREMIUM_CUSTOMER  \
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1             150         RRD  YOUNG SINGLES/COUPLES       Mainstream
2             210     GRNWVES         YOUNG FAMILIES           Budget
3             175     NATURAL         YOUNG FAMILIES           Budget
4             160  WOOLWORTHS  OLDER SINGLES/COUPLES       Mainstream
…             …          …                    …              …
264829        210     GRNWVES         YOUNG FAMILIES       Mainstream
264830        150      KETTLE         YOUNG FAMILIES          Premium
264831        165    TYRRELLS         OLDER FAMILIES           Budget
264832        300         OLD         OLDER FAMILIES           Budget
264833        330      SMITHS  YOUNG SINGLES/COUPLES       Mainstream

        YEARMONTH
0          201810
1          201809
2          201903
3          201903
4          201811
…            …
264829     201812
264830     201810
264831     201810
264832     201810
264833     201812

[264834 rows x 13 columns]
```

Next, we want to create a function that will be able to calculate the total sales, number of customers, transactions per customer, chips per customer and the average price per unit for each store and month.

[4]:
```python
# Define the metrics and calculate them
grouped_df = df.groupby(["STORE_NBR","YEARMONTH"])
tot_sales = grouped_df.TOT_SALES.sum()
n_cust = grouped_df.LYLTY_CARD_NBR.nunique()
ntrans_percust = grouped_df.TXN_ID.size()/n_cust
nchips_pertrans = grouped_df.PROD_QTY.sum()/grouped_df.TXN_ID.size()
avg_priceperunit = tot_sales/grouped_df.PROD_QTY.sum()
# Put the metrics together in an array
metric_arrays =  [tot_sales, n_cust, ntrans_percust, nchips_pertrans,␣
 ↪avg_priceperunit]

# Create the metrics table fro mthe array
metrics_df = pd.concat(metric_arrays, axis=1)
# Give the columns labels
metrics_df.columns = ['tot_sales', 'n_cust', 'ntrans_percust',␣
 ↪'nchips_pertrans', 'avg_priceperunit']
metrics_df = metrics_df.reset_index()
```

[94]:
```python
# Filter to select the stores with full observation periods
month_counts = metrics_df.groupby('STORE_NBR').YEARMONTH.nunique().reset_index()
stores_fullobs = month_counts[month_counts.YEARMONTH ==12].STORE_NBR
pretrial_metrics = metrics_df[metrics_df['STORE_NBR'].isin(stores_fullobs)]

# Then filter to keep only the pre-trial period data
pretrial_metrics = pretrial_metrics.loc[pretrial_metrics.YEARMONTH < 201902]
pretrial_metrics
```

[94]:
```
      STORE_NBR  YEARMONTH  tot_sales  n_cust  ntrans_percust  \
0             1     201807      206.9      49        1.061224
1             1     201808      176.1      42        1.023810
2             1     201809      278.8      59        1.050847
3             1     201810      188.1      44        1.022727
4             1     201811      192.6      46        1.021739
…           …          …         …       …             …
3159        272     201809      304.7      32        1.125000
3160        272     201810      430.6      44        1.159091
3161        272     201811      376.2      41        1.097561
3162        272     201812      403.9      47        1.000000
3163        272     201901      423.0      46        1.086957

      nchips_pertrans  avg_priceperunit
0            1.192308          3.337097
1            1.255814          3.261111
2            1.209677          3.717333
3            1.288889          3.243103
4            1.212766          3.378947
…                 …                 …
```

```
3159         1.972222         4.291549
3160         1.941176         4.349495
3161         1.933333         4.324138
3162         1.893617         4.538202
3163         1.920000         4.406250

[1820 rows x 7 columns]
```

Now we need to work out a way of ranking how similar each potential control store is to the trial store. We can calculate how correlated the performance of each potential control store is to the trial store.

[6]:
```
# Write a function to calculate the correlation between a trial store and all␣
↪possible control stores
# Inputs:
    # trial (int) : the trial store to test
    # metric_col (str) : the label of the metric column to correlate
    # input_table (df) : the full data table of metrics to obtain the␣
↪correlations with
# Output:
    # corr_table (df) : a data frame with the year-month, trial store, control␣
↪store and their correlation

def calc_corr(trial, metric_col, input_table = pretrial_metrics):
    trial_stores = [77, 86, 88]
    control_stores = stores_fullobs[~stores_fullobs.isin(trial_stores)] # all␣
↪stores but trial stores
    # Keep the trial store values to perform correlation with
    trial_vals = input_table[input_table["STORE_NBR"] == trial][metric_col].
↪reset_index()
    corr_table = pd.DataFrame(columns = ['YEARMONTH', 'trial_store',␣
↪'control_store', 'correlation'])
    # Find the correlation for each control store
    for control in control_stores:
        # Keep the control store values to perform correlation with
        control_vals = input_table[input_table["STORE_NBR"] ==␣
↪control][metric_col].reset_index()
        corr_row = pd.DataFrame(columns = ['YEARMONTH', 'trial_store',␣
↪'control_store', 'correlation'])
        corr_row.YEARMONTH = list(input_table.loc[input_table.STORE_NBR ==␣
↪control]["YEARMONTH"])
        corr_row.trial_store = trial
        corr_row.control_store = control
        corr_row.correlation = control_vals.corrwith(trial_vals, axis=1)
        corr_table = pd.concat([corr_table, corr_row]) # add each store's block␣
↪to the dataframe
    return (corr_table)
```

[7]:
```
trial_stores = [77, 86, 88]
corr_table = pd.DataFrame(columns = ['YEARMONTH', 'trial_store',
 ↪'control_store', 'correlation'])
for store in trial_stores:
    corr_section = calc_corr(store, ['tot_sales', 'n_cust', 'ntrans_percust',
 ↪'nchips_pertrans', 'avg_priceperunit'] )
    corr_table = pd.concat([corr_table, corr_section])
```

[8]:
```
corr_table
```

[8]:
```
   YEARMONTH trial_store control_store  correlation
0     201807          77             1     0.070544
1     201808          77             1     0.027332
2     201809          77             1     0.002472
3     201810          77             1    -0.019991
4     201811          77             1     0.030094
..       …           …             …           …
2     201809          88           272     0.533160
3     201810          88           272     0.591056
4     201811          88           272     0.566378
5     201812          88           272     0.594442
6     201901          88           272     0.621775

[5397 rows x 4 columns]
```

Apart from correlation, we can also calculate a standardised metric based on the absolute difference between the trial store's performance and each control store's performance. Write a function to calculate the magnitude distance.

[9]:
```
# Write a function to calculate the normalised distance magnitude between a
 ↪trial store and all possible control stores
# Inputs:
    # trial (int) : the trial store to test
    # metric_col (str) : the label of the metric column to correlate
    # input_table (df) : the full data table of metrics to obtain the
 ↪correlations with
# Output:
    # corr_table (df) : a data frame with the year-month, trial store, control
 ↪store and their normalised distance

def calc_magdist(trial, metric_col, input_table = pretrial_metrics):
    trial_stores = [77, 86, 88]
    control_stores = stores_fullobs[~stores_fullobs.isin(trial_stores)] # all
 ↪stores but the trials
    dist_table = pd.DataFrame() # to store the distances for each store and
 ↪month
    for control in control_stores: # calculate for each control store
```

```
        dist_row = pd.DataFrame()
        # Calculate the distance as an absolute value
        dist_row = abs(input_table[input_table["STORE_NBR"] == trial].
 ↪reset_index()[metric_col]\
                        - input_table[input_table["STORE_NBR"] == control].
 ↪reset_index()[metric_col])
        dist_row.insert(0,'YEARMONTH', list(input_table.loc[input_table.
 ↪STORE_NBR == trial]["YEARMONTH"]))
        dist_row.insert(1,'trial_store', trial)
        dist_row.insert(2,'control_store', control)
        dist_table = pd.concat([dist_table, dist_row])

    for col in metric_col: # then loop over each column to find the max and min
 ↪distances to normalise
        maxdist = dist_table[col].max()
        mindist = dist_table[col].min()
        dist_table[col] = 1-(dist_table[col] - mindist)/(maxdist-mindist) #
 ↪normalised distance measure
        # also give an average magnitude over all metrics per month and store
 ↪pair
    dist_table['mag_measure'] = dist_table[metric_col].mean(axis=1)
    return (dist_table)
```

Now we will use the functions to find the control stores! 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. So we will need to use our functions to get four scores, two for each of total sales and total customers.

[27]:
```
# Write a function to generate a table of averaged correlations, distance and
 ↪scores over the pretrial months for each store
# Inputs:
    # trial (int) : the trial store to test
    # metric_col (str) : the metric label to calculate the scores for
    # input_table (df) : the data to calculate the scores with in the pre-trial
 ↪period
# Output:
    # avg_corrmag (df) : a table with the correlations, distance and scores
 ↪averaged over the pretrial months for each store
def calc_corrdist_score (trial, metric_col, input_table=pretrial_metrics):
    # Calculate the correlations and magnitudes for all months
    corr_vals = calc_corr(trial, metric_col, input_table)
    mag_vals = calc_magdist(trial, metric_col, input_table)
    mag_vals = mag_vals.drop(metric_col, axis=1) # For one metric, the two
 ↪columns will be duplicates so drop one

    # Combine correlations and magnitudes together to one df
```

```
    combined_corr_dist = pd.merge(corr_vals, mag_vals, on=["YEARMONTH", "trial_store", "control_store"])

    # Average correlations and distances over the pre-trial months
    avg_corrmag = combined_corr_dist.groupby(["trial_store", "control_store"]).mean().reset_index()

    # Find a combined score by taking the weighted average of the correlations and magnitudes
    corr_weight = 0.5
    avg_corrmag['combined_score'] = corr_weight*avg_corrmag['correlation'] + (1-corr_weight)*avg_corrmag['mag_measure']

    return(avg_corrmag)
```

[32]:

```
# Write a function to output the 5 stores with the highest averaged scores combining the tot_sales and n_cust metrics
# for a given trial store over the pre-trial period
# Inputs:
    # trial (int) : the trial store to test
# Output:
    # scores (df) : a sorted table with the 5 highest composite scores of possible control stores

def find_highestscore(trial):
    # Obtain the scores for the tot_sales and n_cust metrics separately
    scores_tot_sales = calc_corrdist_score (trial, ['tot_sales'])
    scores_n_cust = calc_corrdist_score (trial, ['n_cust'])
    # Create a data table to store the composite results in - stores are also
    scores_control = pd.DataFrame()
    scores_control['control_store'] = scores_tot_sales.control_store
    # Calculate the composite scores
    scores_control['correlation'] = 0.5*scores_tot_sales.correlation + 0.5*scores_n_cust.correlation
    scores_control['mag_measure'] = 0.5*scores_tot_sales.mag_measure + 0.5*scores_n_cust.mag_measure
    scores_control['scores'] = 0.5*scores_tot_sales.combined_score + 0.5*scores_n_cust.combined_score
    return(scores_control.sort_values(by = 'scores', ascending = False).reset_index(drop = True).head(5))
```

[29]:

```
# Now find the control stores with the highest scores for each of the trial stores
trial_stores = [77, 86, 88]
for trial in trial_stores:
    print('Trial store: ', trial)
```

```
    print(find_highestscore(trial))
    print()
```

```
Trial store:  77
   control_store  correlation  mag_measure    scores
0            233          1.0     0.989804  0.994902
1             41          1.0     0.972041  0.986020
2             46          1.0     0.969523  0.984762
3             53          1.0     0.968421  0.984211
4            111          1.0     0.967981  0.983991

Trial store:  86
   control_store  correlation  mag_measure    scores
0            155          1.0     0.976324  0.988162
1            109          1.0     0.968180  0.984090
2            225          1.0     0.965044  0.982522
3            229          1.0     0.957995  0.978997
4            101          1.0     0.945394  0.972697

Trial store:  88
   control_store  correlation  mag_measure    scores
0             40          1.0     0.941789  0.970895
1             26          1.0     0.917859  0.958929
2             72          1.0     0.908157  0.954079
3             58          1.0     0.900435  0.950217
4             81          1.0     0.887572  0.943786
```

From the above output, the stores with the highest scores are:

- Store 233 for trial store 77
- Store 155 for trial store 86
- Store 40 for trial stre 88

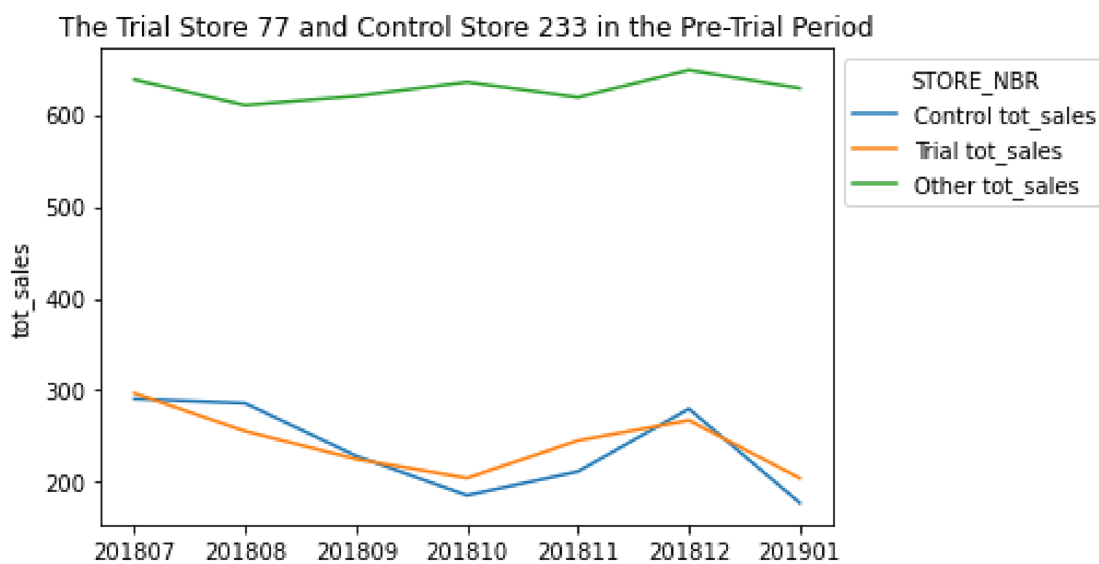
Note that the combined store for the control cases of trial store 88 are lower than those of stores 77 and 86. This may suggest that the control stores may not match store 88 as well as for the other trial stores.

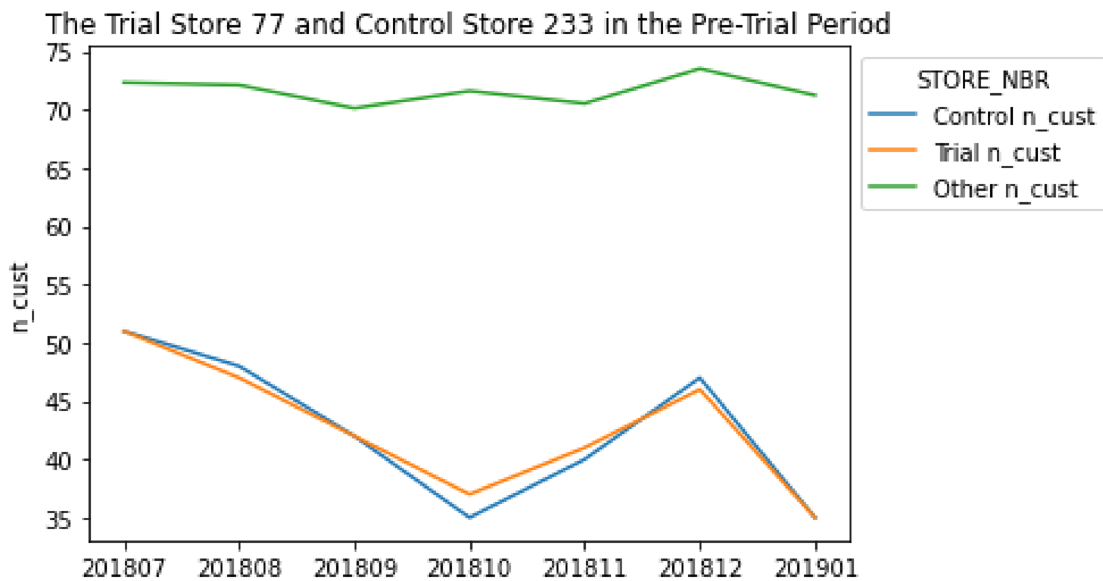
Now that we have found the control stores, we can visually check if the drivers are similar between these and the trial stores in the pre-trial period.

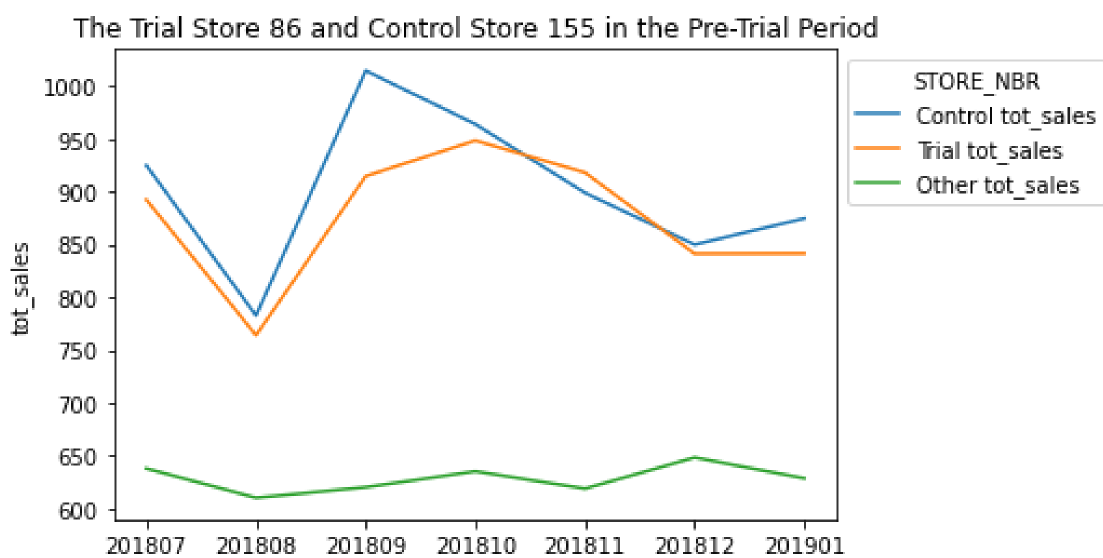
[119]:
```
def make_plots(storepair, metric_col):
    trial = storepair[0]
    control = storepair[1]
    trial_plot = pretrial_metrics[pretrial_metrics.STORE_NBR ==␣
 ↪trial][['YEARMONTH', 'STORE_NBR', metric_col]]
    trial_plot = trial_plot.rename(columns = {metric_col: metric_col+'_trial'})
    control_plot = pretrial_metrics[pretrial_metrics.STORE_NBR ==␣
 ↪control][['YEARMONTH', 'STORE_NBR', metric_col]]
```

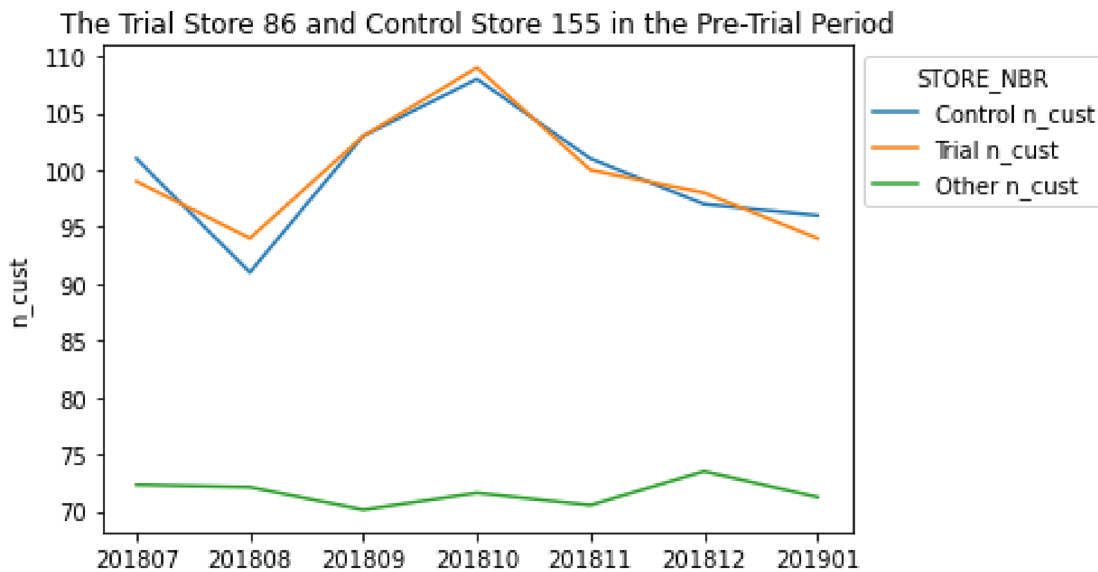
```python
    control_plot = control_plot.rename(columns = {metric_col: metric_col+'_control'})

    other_stores = pretrial_metrics.loc[(pretrial_metrics.STORE_NBR != 77)][['YEARMONTH', 'STORE_NBR', metric_col]]
    other_stores = other_stores.loc[(pretrial_metrics.STORE_NBR != 233)]
    plot_other = other_stores.groupby('YEARMONTH')[metric_col].mean()

    ax = control_plot.plot.line(x = "YEARMONTH", y = metric_col+'_control', use_index=False, label = 'Control '+metric_col)
    ax_trial = trial_plot.plot.line(x = "YEARMONTH", y = metric_col+'_trial', use_index=False, ax=ax, label = 'Trial '+metric_col)
    ax_other = plot_other.plot.line(use_index = False, ax=ax, label = 'Other '+ metric_col)
    ax.set_ylabel(metric_col)
    plt.legend(title = 'STORE_NBR', loc = "upper left",bbox_to_anchor=(1.0, 1.0))
    positions = (0,1,2,3,4,5,6)
    labels = ("201807", '201808', '201809', '201810', '201811', '201812', '201901')
    plt.xticks (positions, labels)
    titlestr = 'The Trial Store ' + str(storepair[0]) + ' and Control Store ' + str(storepair[1]) + ' in the Pre-Trial Period'
    ax.set_title(titlestr)
```

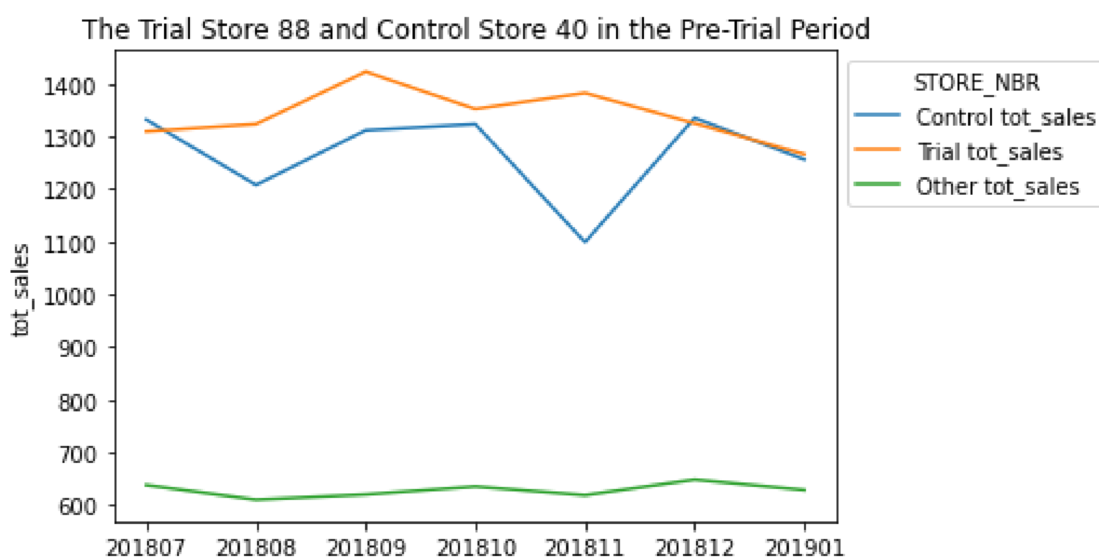
[120]:
```python
storepair = [[77, 233], [86, 155], [88, 40]]
metric_col = ['tot_sales', 'n_cust']
for pair in storepair:
    for metric in metric_col:
        make_plots(pair, metric)
```

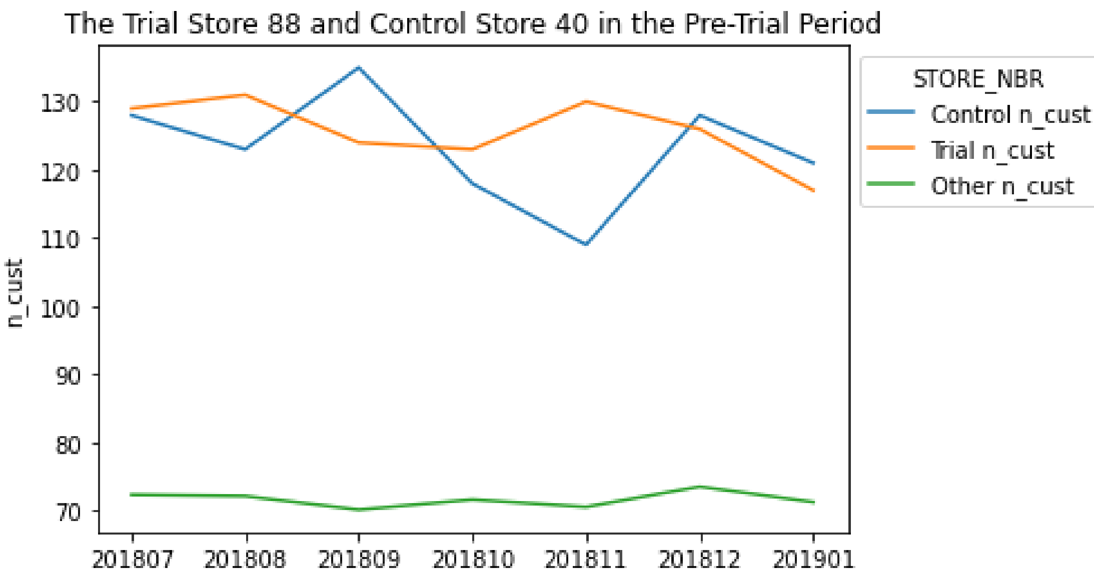



The Trial Store 77 and Control Store 233 in the Pre-Trial Period
STORE_NBR
Control n_cust
Trial n_cust
Other n_cust
n_cust
75
70
65
60
55
50
45
40
35
201807
201808
201809
201810
201811
201812
201901


The Trial Store 86 and Control Store 155 in the Pre-Trial Period
STORE_NBR
Control tot_sales
Trial tot_sales
Other tot_sales
tot_sales
1000
950
900
850
800
750
700
650
600
201807
201808
201809
201810
201811
201812
201901


The Trial Store 86 and Control Store 155 in the Pre-Trial Period
n_cust
110
105
100
95
90
85
80
75
70
201807
201808
201809
201810
201811
201812
201901
STORE_NBR
Control n_cust
Trial n_cust
Other n_cust


The Trial Store 88 and Control Store 40 in the Pre-Trial Period
tot_sales
1400
1300
1200
1100
1000
900
800
700
600
201807
201808
201809
201810
201811
201812
201901
STORE_NBR
Control tot_sales
Trial tot_sales
Other tot_sales



The metrics of the control and trial stores look reasonably similar in the pre-trial period.

Now, we want to see if there has been an uplift in overall chip sales. We'll start with scaling the control store's sales to a level similar to control for any differences between the two stores outside of the trial period.

[33]:
```
# Calculate the scaling factor for the store pairs
scale_store77 = pretrial_metrics[pretrial_metrics.STORE_NBR == 77]['tot_sales'].
 ↪sum()/pretrial_metrics[pretrial_metrics.STORE_NBR == 233]['tot_sales'].sum()
scale_store86 = pretrial_metrics[pretrial_metrics.STORE_NBR == 86]['tot_sales'].
 ↪sum()/pretrial_metrics[pretrial_metrics.STORE_NBR == 155]['tot_sales'].sum()
scale_store88 = pretrial_metrics[pretrial_metrics.STORE_NBR == 88]['tot_sales'].
 ↪sum()/pretrial_metrics[pretrial_metrics.STORE_NBR == 40]['tot_sales'].sum()
```

[34]:
```
# Extract the control store data from the df and scale according to the store
scaled_control233 = metrics_df[metrics_df.STORE_NBR.isin([233])][['STORE_NBR',␣
 ↪"YEARMONTH", 'tot_sales']]
scaled_control233.tot_sales *= scale_store77
scaled_control155 = metrics_df[metrics_df.STORE_NBR.isin([155])][['STORE_NBR',␣
 ↪"YEARMONTH", 'tot_sales']]
scaled_control155.tot_sales *= scale_store86
scaled_control40 = metrics_df[metrics_df.STORE_NBR.isin([40])][['STORE_NBR',␣
 ↪"YEARMONTH", 'tot_sales']]
scaled_control40.tot_sales *= scale_store88

# Combine the scaled control stores to a single df
scaledsales_control = pd.concat([scaled_control233, scaled_control155,␣
 ↪scaled_control40]).reset_index(drop = True)
```

```
scaledsales_control = scaledsales_control.rename(columns = {'tot_sales':
 ↪'scaled_tot_sales', 'STORE_NBR': 'CONTROL_NBR'})
# Get the trial period of scaled control stores
scaledsales_control_trial = scaledsales_control[(scaledsales_control.
 ↪YEARMONTH>=201902) & (scaledsales_control.YEARMONTH<=201904)].
 ↪reset_index(drop = True)

# Get the trial period of the trial stores
trialsales = metrics_df[metrics_df.STORE_NBR.isin([77,86,88])][['STORE_NBR',␣
 ↪"YEARMONTH", 'tot_sales']].reset_index(drop = True)
trialsales = trialsales.rename(columns = {'STORE_NBR': 'TRIAL_NBR'})
trialsales_trial = trialsales[(trialsales.YEARMONTH >= 201902) & (trialsales.
 ↪YEARMONTH <= 201904)].reset_index(drop = True)
```

Now that we have comparable sales figures for the control store, we can calculate the percentage difference between the scaled control sales and the trial store's sales during the trial period.

[38]:
```
# Calculate the percentage difference between the control and trial store pairs␣
 ↪for each month over the year
percentdiff = scaledsales_control.copy()
percentdiff[['TRIAL_NBR', 'tot_sales_t']] = trialsales[['TRIAL_NBR',␣
 ↪'tot_sales']]
percentdiff = percentdiff.rename(columns = {'scaled_tot_sales' :␣
 ↪'scaled_sales_c'})
percentdiff['sales_percent_diff'] = (percentdiff.tot_sales_t-percentdiff.
 ↪scaled_sales_c)\
                                    /(0.5*((percentdiff.
 ↪scaled_sales_c+percentdiff.tot_sales_t)))
percentdiff.head()
```

[38]:
```
   CONTROL_NBR  YEARMONTH  scaled_sales_c  TRIAL_NBR  tot_sales_t  \
0          233     201807      297.565550         77        296.8
1          233     201808      292.652187         77        255.5
2          233     201809      233.998916         77        225.2
3          233     201810      190.085733         77        204.5
4          233     201811      216.597421         77        245.3

   sales_percent_diff
0           -0.002576
1           -0.135554
2           -0.038323
3            0.073060
4            0.124281
```

Let's see if the difference is significant using a t-test. Our null hypothesis is that the trial period is the same as the pre-trial period; we will test with a null hypothesis that there is a 0-percent between the trial and control stores.

[39]:
```
# As our null hypothesis is that the trial period is the same as the pre-trial␣
↪period,
# let's take the standard deviation based on the scaled percentage difference␣
↪in the pre-trial period.
pretrial_percentdiff = percentdiff[percentdiff.YEARMONTH < 201902]
pretrial_percentdiff_std = pretrial_percentdiff.
↪groupby(['TRIAL_NBR'])['sales_percent_diff'].agg('std').reset_index()
dof = 6 # 7 months of data - 1

for stores in storepair: # stores numbers are stored as [trial, control] in␣
↪storepair
    trialstore = stores[0]
    controlstore = stores[1]
    pretrial = percentdiff[(percentdiff.YEARMONTH < 201902) & (percentdiff.
↪TRIAL_NBR == trialstore)]
    std = pretrial['sales_percent_diff'].agg('std')
    mean =  pretrial['sales_percent_diff'].agg('mean')
    trialperiod = percentdiff[(percentdiff.YEARMONTH >= 201902) & (percentdiff.
↪YEARMONTH <= 201904) \
                              & (percentdiff.TRIAL_NBR == trialstore)]
    print("Trial store -", trialstore, "; control store -", controlstore)
    print("Month : t-statistic")
    for month in trialperiod.YEARMONTH.unique():
        xval = trialperiod[trialperiod.YEARMONTH ==␣
↪month]['sales_percent_diff'].item()
        tstat = ((xval - mean)/std)
        print(str(month), ' : ', tstat)
    print()

# Generate the t-statistic for the 95% percentile with 6 dof
print ('95th percentile value:', stats.t.ppf(1-0.05, 6))
```

```
Trial store - 77 ; control store - 233
Month : t-statistic
201902  :  -0.7171038288055888
201903  :  3.035317928855662
201904  :  4.708944418758203

Trial store - 86 ; control store - 155
Month : t-statistic
201902  :  1.4133618775921797
201903  :  7.123063846042149
201904  :  0.8863824572944162

Trial store - 88 ; control store - 40
Month : t-statistic
201902  :  -0.5481633746817604
```

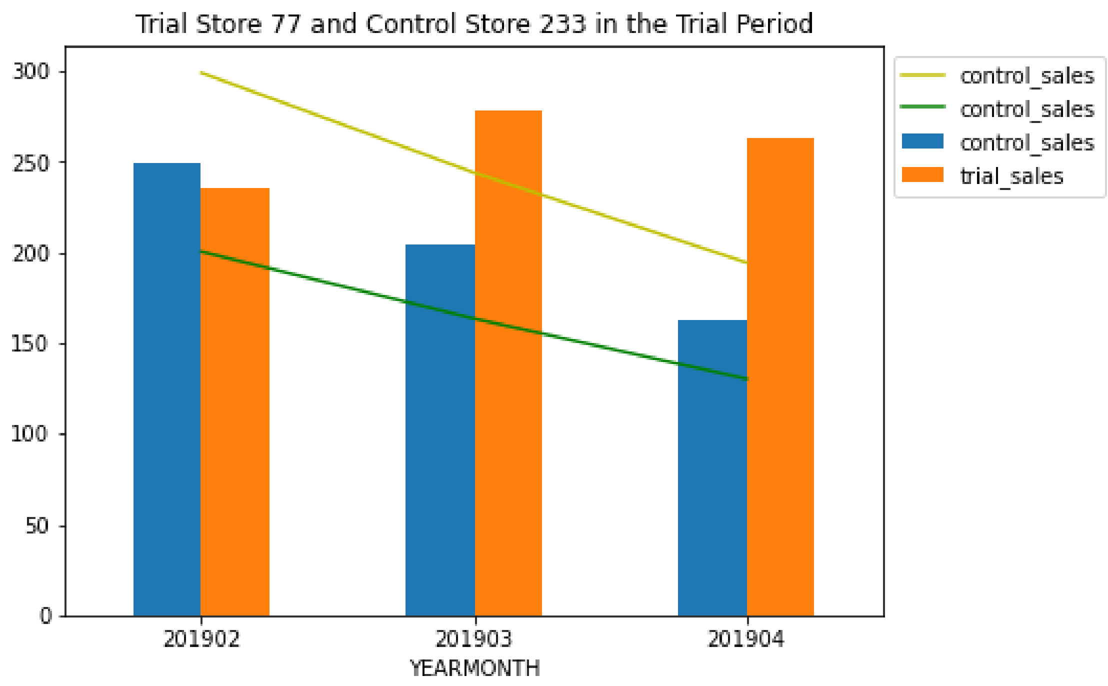
```
201903  :  1.0089992743637755
201904  :  0.9710006270463645

95th percentile value: 1.9431802803927816
```

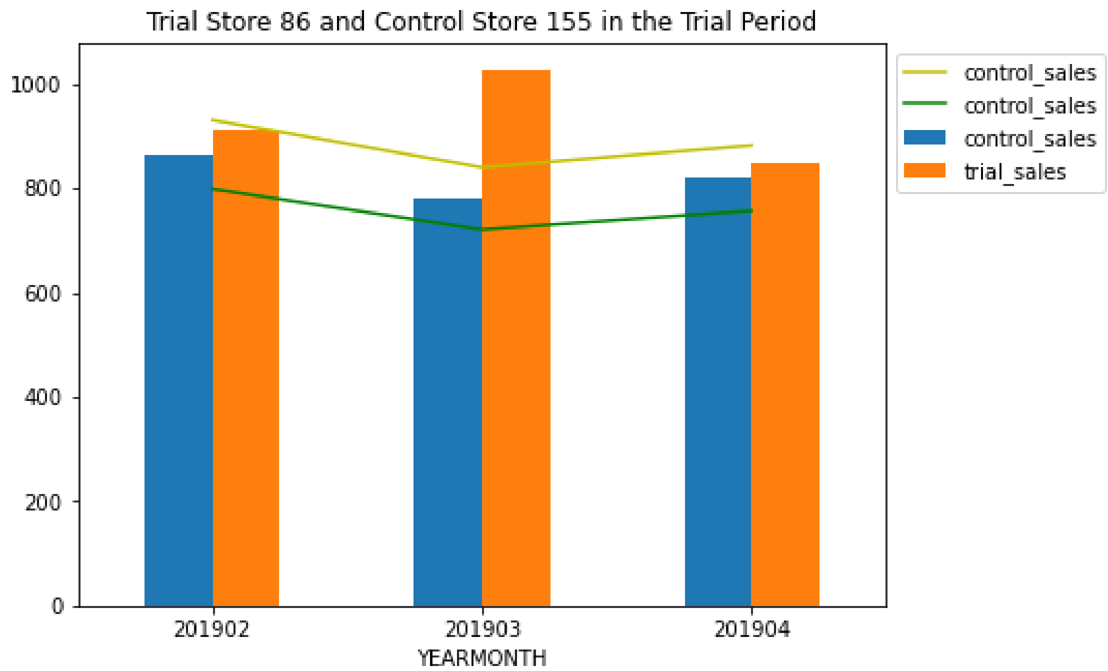
We can observe that the t-value for the trial store 77 is much larger than the 95th percentile value of the t-distribution for March and April - i.e. the increase in sales in the trial store 77 in March and April is statistically greater than in the control store. This can also be seen for March of trial store 86.

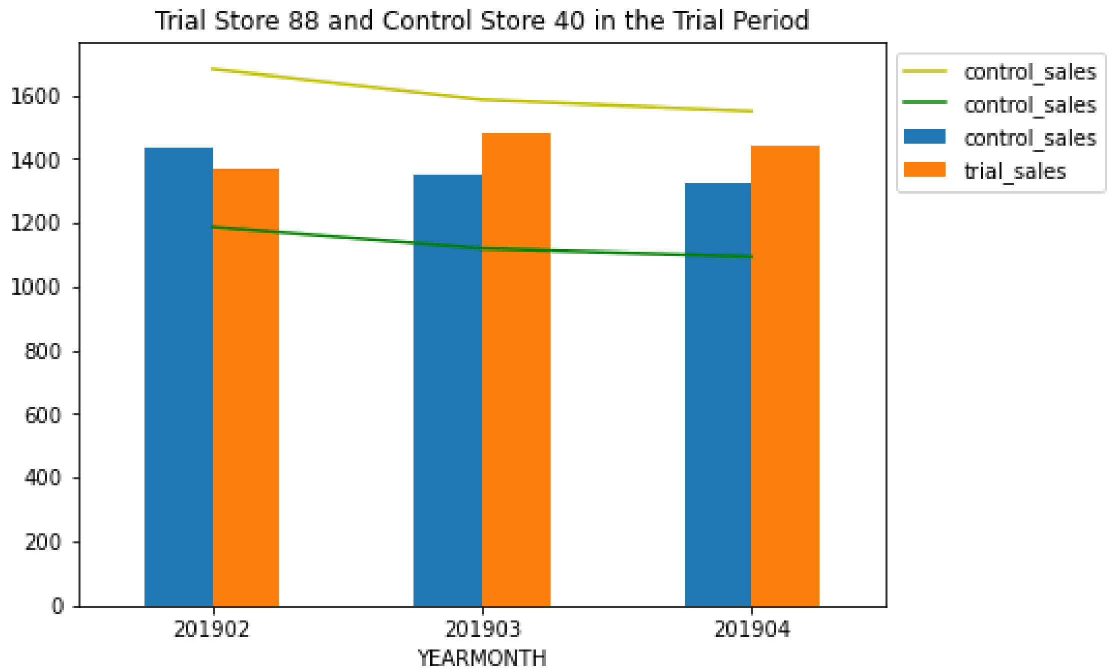
Let's create a more visual version of this by plotting the sales of the control store, the sales of the trial stores and the 95th percentile value of sales of the control store.

[41]:
```
# First do bar graphs during the trial period
storepair = [[77, 233], [86, 155], [88, 40]]
for stores in storepair: # stores numbers are stored as [trial, control] in␣
 ↪storepair
    trial = stores[0]
    control = stores[1]

    # Plot the bar chart of sales performance
    plot_control = percentdiff[(percentdiff['CONTROL_NBR'] == control) &␣
 ↪(percentdiff.YEARMONTH >= 201902) & (percentdiff.YEARMONTH <= 201904)]\
                     [['YEARMONTH', 'CONTROL_NBR', 'scaled_sales_c']]
    plot_control = plot_control.rename(columns = {"CONTROL_NBR" : "STORE_NBR",␣
 ↪"scaled_sales_c": "control_sales"})
    plot_trial = percentdiff[(percentdiff['TRIAL_NBR'] == trial) & (percentdiff.
 ↪YEARMONTH >= 201902) & (percentdiff.YEARMONTH <= 201904)]\
                     [['YEARMONTH', 'TRIAL_NBR', 'tot_sales_t']]
    plot_trial = plot_trial.rename(columns = {"TRIAL_NBR" : "STORE_NBR",␣
 ↪"tot_sales_t": "trial_sales"})
    toplot = plot_control[["YEARMONTH", "control_sales"]].
 ↪merge(plot_trial[["YEARMONTH", "trial_sales"]],on="YEARMONTH").
 ↪set_index("YEARMONTH")
    ax = toplot.plot(kind = 'bar',  figsize=(7, 5))


    # plot the thresholds as lines
    std = percentdiff[(percentdiff['CONTROL_NBR'] == control) & (percentdiff.
 ↪YEARMONTH < 201902)]['sales_percent_diff'].std()
    threshold95 = plot_control.reset_index()[['YEARMONTH', 'control_sales']]
    threshold95.control_sales = threshold95.control_sales*(1+std*2)
    threshold5 = plot_control.reset_index()[['YEARMONTH', 'control_sales']]
    threshold5.control_sales = threshold5.control_sales*(1-std*2)
    ax95 = threshold95.plot.line(x = 'YEARMONTH', y =␣
 ↪'control_sales',color='y', figsize=(7, 5), use_index=False, ax = ax)
    ax5 = threshold5.plot.line(x = 'YEARMONTH', y = 'control_sales', color='g',␣
 ↪figsize=(7, 5), use_index=False, ax = ax)
```

```
    # Other plot features
    plt.legend(loc = "upper left",bbox_to_anchor=(1.0, 1.0))
    titlestr = 'Trial Store ' + str(trial) + ' and Control Store ' +␣
↪str(control) + ' in the Trial Period'
    ax.set_title(titlestr)
    plt.show()
```



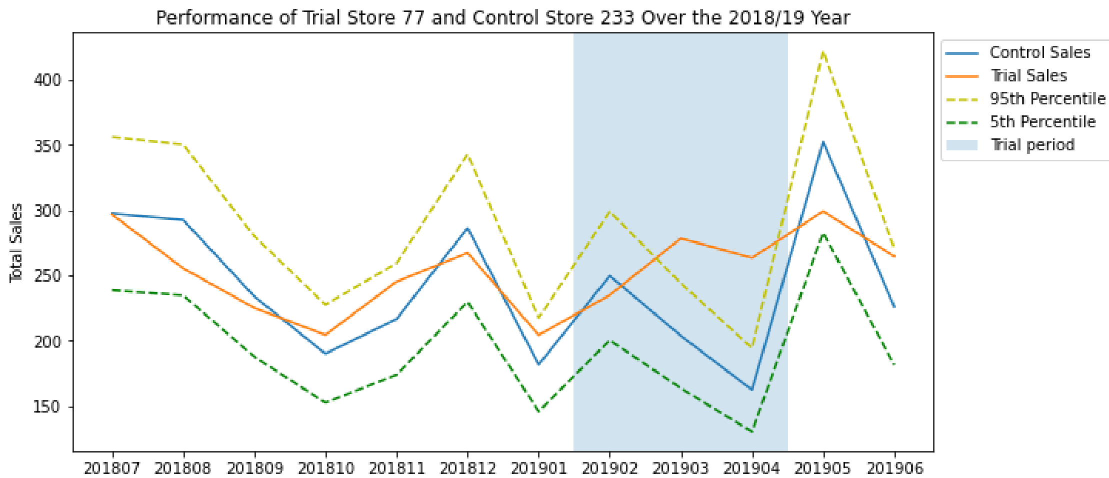


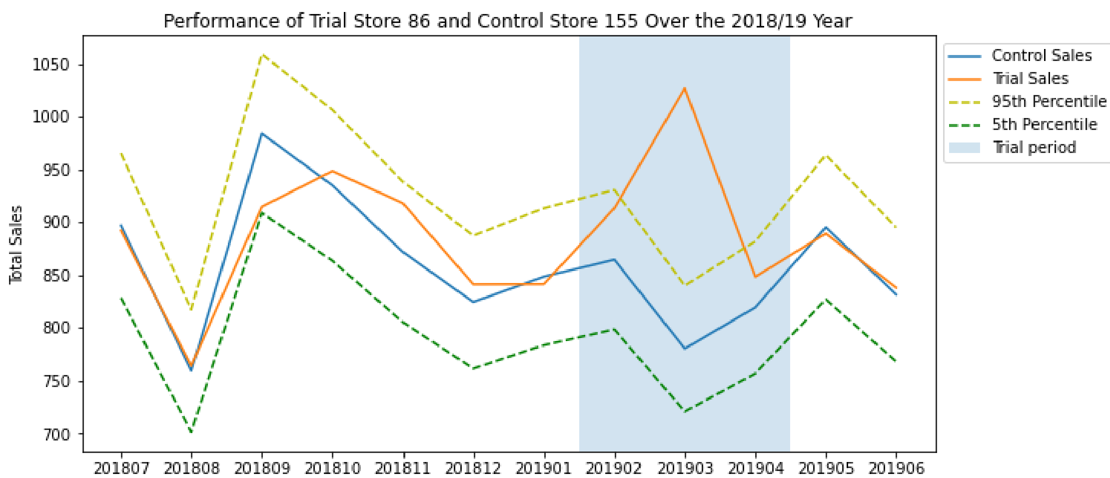


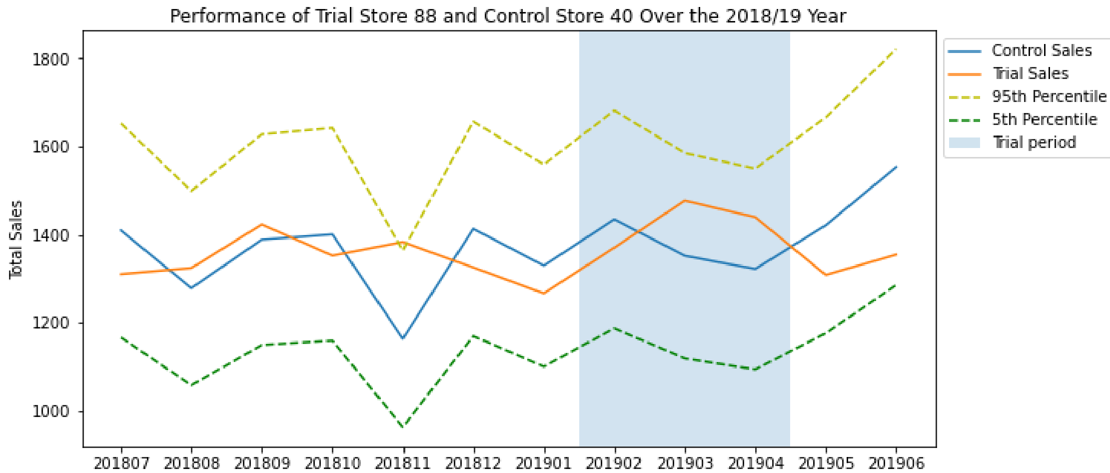
[79]:
```
# Then do line graphs during the whole year - for the report
from matplotlib.patches import Rectangle
storepair = [[77, 233], [86, 155], [88, 40]]
```

```python
for stores in storepair: # stores numbers are stored as [trial, control] in storepair
    trial = stores[0]
    control = stores[1]

    # Plot the line graph of sales performance
    plot_control = percentdiff[(percentdiff['CONTROL_NBR'] == control)][['YEARMONTH', 'CONTROL_NBR', 'scaled_sales_c']]
    plot_control = plot_control.rename(columns = {"CONTROL_NBR" : "STORE_NBR", "scaled_sales_c": "control_sales"})
    plot_trial = percentdiff[(percentdiff['TRIAL_NBR'] == trial)][['YEARMONTH', 'TRIAL_NBR', 'tot_sales_t']]
    plot_trial = plot_trial.rename(columns = {"TRIAL_NBR" : "STORE_NBR", "tot_sales_t": "trial_sales"})

    ax = plot_control.plot.line(x = "YEARMONTH", y = 'control_sales', use_index=False, label = 'Control Sales')
    ax_trial = plot_trial.plot.line(x = "YEARMONTH", y = 'trial_sales', use_index=False, ax=ax, label = 'Trial Sales')


    # plot the thresholds as lines
    std = percentdiff[(percentdiff['CONTROL_NBR'] == control) & (percentdiff.YEARMONTH < 201902)]['sales_percent_diff'].std()
    threshold95 = plot_control.reset_index()[['YEARMONTH', 'control_sales']]
    threshold95.control_sales = threshold95.control_sales*(1+std*2)
    threshold5 = plot_control.reset_index()[['YEARMONTH', 'control_sales']]
    threshold5.control_sales = threshold5.control_sales*(1-std*2)
    ax95 = threshold95.plot.line(x = 'YEARMONTH', y = 'control_sales',color='y', linestyle = '--', figsize=(10, 5), use_index=False, ax = ax, label = '95th Percentile')
    ax5 = threshold5.plot.line(x = 'YEARMONTH', y = 'control_sales', color='g', linestyle = '--', figsize=(10, 5), use_index=False, ax = ax, label = '5th Percentile')
    ax.add_patch(Rectangle((6.5, 0), 3, 2000, alpha = 0.2, label = 'Trial period'))

    # Other plot features
    ax.set_ylabel('Total Sales')
    plt.legend(loc = "upper left",bbox_to_anchor=(1.0, 1.0))
    titlestr = 'Performance of Trial Store ' + str(trial) + ' and Control Store ' + str(control) + ' Over the 2018/19 Year'
    positions = (0,1,2,3,4,5,6,7,8,9, 10, 11)
    labels = ("201807", '201808', '201809', '201810', '201811', '201812', '201901', '201902', '201903', '201904', '201905', '201906')
    plt.xticks (positions, labels)
```

```
    ax.set_title(titlestr)
    plt.show()
```







The results show that the trial in store 77 is significantly different to its control store in the trial period as the trial store performance lies outside the 5% to 95% confidence interval of the control store in two of the three trial months.

For store 86, we can see that the trial in March is significantly different to the control store with the total sales performance outside of the 5% to 95% confidence interval. However, there is no significant difference in February's and April's performance.

The results for store 88 show no significant difference between the trial and control stores during this period.

Let's have a look at assessing this for number of customers as well.

[80]:
```
# Calculate the scaling factor for the store pairs
scale_store77 = pretrial_metrics[pretrial_metrics.STORE_NBR == 77]['n_cust'].
 ↪sum()/pretrial_metrics[pretrial_metrics.STORE_NBR == 233]['n_cust'].sum()
scale_store86 = pretrial_metrics[pretrial_metrics.STORE_NBR == 86]['n_cust'].
 ↪sum()/pretrial_metrics[pretrial_metrics.STORE_NBR == 155]['n_cust'].sum()
scale_store88 = pretrial_metrics[pretrial_metrics.STORE_NBR == 88]['n_cust'].
 ↪sum()/pretrial_metrics[pretrial_metrics.STORE_NBR == 40]['n_cust'].sum()
```

[81]:
```
# Extract the control store data from the df and scale according to the store
scaled_control233 = metrics_df[metrics_df.STORE_NBR.isin([233])][['STORE_NBR',␣
 ↪"YEARMONTH", 'n_cust']]
scaled_control233.n_cust *= scale_store77
scaled_control155 = metrics_df[metrics_df.STORE_NBR.isin([155])][['STORE_NBR',␣
 ↪"YEARMONTH", 'n_cust']]
scaled_control155.n_cust *= scale_store86
scaled_control40 = metrics_df[metrics_df.STORE_NBR.isin([40])][['STORE_NBR',␣
 ↪"YEARMONTH", 'n_cust']]
scaled_control40.n_cust *= scale_store88
```

```
# Combine the scaled control stores to a single df
scaledncust_control = pd.concat([scaled_control233, scaled_control155,␣
 ↪scaled_control40]).reset_index(drop = True)
scaledncust_control = scaledncust_control.rename(columns = {'n_cust':
 ↪'scaled_n_cust', 'STORE_NBR': 'CONTROL_NBR'})
# Get the trial period of scaled control stores
scaledncust_control_trial = scaledncust_control[(scaledsales_control.
 ↪YEARMONTH>=201902) & (scaledsales_control.YEARMONTH<=201904)].
 ↪reset_index(drop = True)

# Get the trial period of the trial stores
trialncust = metrics_df[metrics_df.STORE_NBR.isin([77,86,88])][['STORE_NBR',␣
 ↪"YEARMONTH", 'n_cust']].reset_index(drop = True)
trialncust = trialncust.rename(columns = {'STORE_NBR': 'TRIAL_NBR'})
trialncust_trial = trialncust[(trialncust.YEARMONTH >= 201902) & (trialsales.
 ↪YEARMONTH <= 201904)].reset_index(drop = True)
```

[82]:
```
# Calculate the percentage difference between the control and trial store pairs␣
 ↪for each month over the year
percentdiff = scaledncust_control.copy()
percentdiff[['TRIAL_NBR', 'n_cust_t']] = trialncust[['TRIAL_NBR', 'n_cust']]
percentdiff = percentdiff.rename(columns = {'scaled_n_cust' :␣
 ↪'scaled_n_cust_c'})
percentdiff['cust_percent_diff'] = (percentdiff.n_cust_t-percentdiff.
 ↪scaled_n_cust_c)\
                                     /(0.5*((percentdiff.
 ↪scaled_n_cust_c+percentdiff.n_cust_t)))
percentdiff.head()
```

[82]:

	CONTROL_NBR	YEARMONTH	scaled_n_cust_c	TRIAL_NBR	n_cust_t	\
0	233	201807	51.171141	77	51	
1	233	201808	48.161074	77	47	
2	233	201809	42.140940	77	42	
3	233	201810	35.117450	77	37	
4	233	201811	40.134228	77	41	

	cust_percent_diff
0	-0.003350
1	-0.024402
2	-0.003350
3	0.052208
4	0.021342

[83]:
```
# As our null hypothesis is that the trial period is the same as the pre-trial␣
 ↪period,
```

```
# let's take the standard deviation based on the scaled percentage difference␣
 ↪in the pre-trial period.
pretrial_percentdiff = percentdiff[percentdiff.YEARMONTH < 201902]
pretrial_percentdiff_std = pretrial_percentdiff.
 ↪groupby(['TRIAL_NBR'])['cust_percent_diff'].agg('std').reset_index()
dof = 6 # 7 months of data - 1

for stores in storepair: # stores numbers are stored as [trial, control] in␣
 ↪storepair
    trialstore = stores[0]
    controlstore = stores[1]
    pretrial = percentdiff[(percentdiff.YEARMONTH < 201902) & (percentdiff.
 ↪TRIAL_NBR == trialstore)]
    std = pretrial['cust_percent_diff'].agg('std')
    mean =  pretrial['cust_percent_diff'].agg('mean')
    trialperiod = percentdiff[(percentdiff.YEARMONTH >= 201902) & (percentdiff.
 ↪YEARMONTH <= 201904) \
                              & (percentdiff.TRIAL_NBR == trialstore)]
    print("Trial store -", trialstore, "; control store -", controlstore)
    print("Month : t-statistic")
    for month in trialperiod.YEARMONTH.unique():
        xval = trialperiod[trialperiod.YEARMONTH == month]['cust_percent_diff'].
 ↪item()
        tstat = ((xval - mean)/std)
        print(str(month), ' : ', tstat)
    print()

# Generate the t-statistic for the 95% percentile with 6 dof
print ('95th percentile value:', stats.t.ppf(1-0.05, 6))
```

```
Trial store - 77 ; control store - 233
Month : t-statistic
201902  :  -0.19886295797440687
201903  :  8.009609025380932
201904  :  16.114474772873923

Trial store - 86 ; control store - 155
Month : t-statistic
201902  :  6.220524882227514
201903  :  10.52599074274189
201904  :  3.0763575852842706

Trial store - 88 ; control store - 40
Month : t-statistic
201902  :  -0.3592881735131531
201903  :  1.2575196020616801
201904  :  0.6092905590514273
```

```
95th percentile value: 1.9431802803927816
```

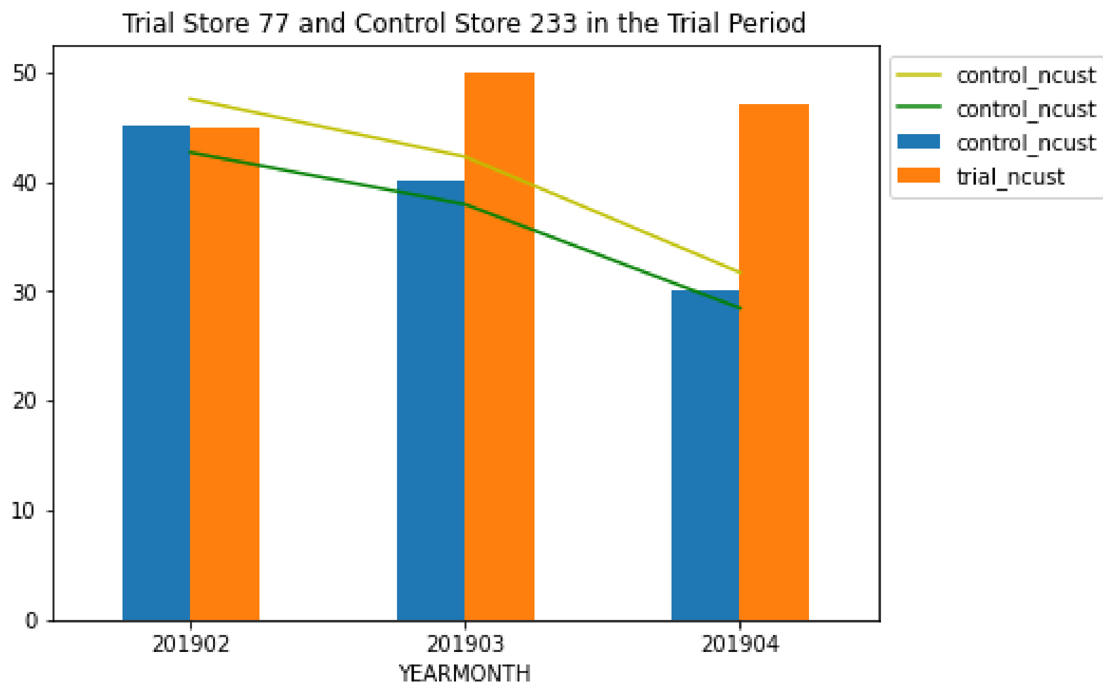
We can see from the above results that similar to the total sales metric, there are statistically significant increases in the number of customers in stores 77 and 86 in at least 2 months during the trial period. However, there is no significant increase in store 88.

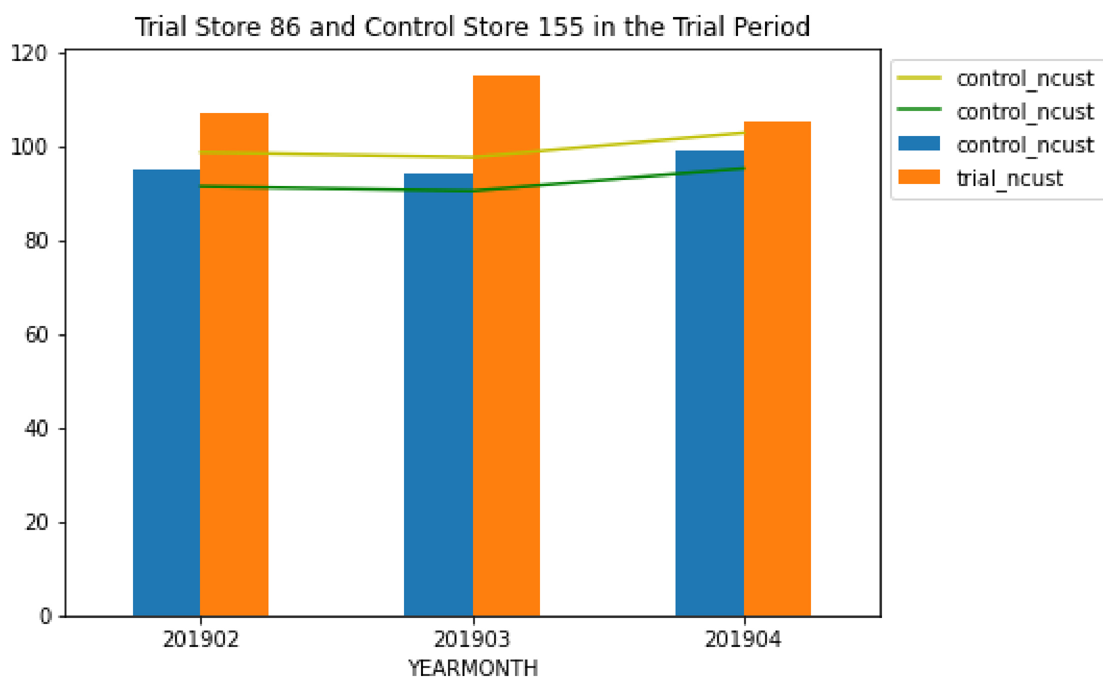
Let's create a more visual version of this by plotting the sales of the control store, the sales of the trial stores and the 95th percentile value of sales of the control store.

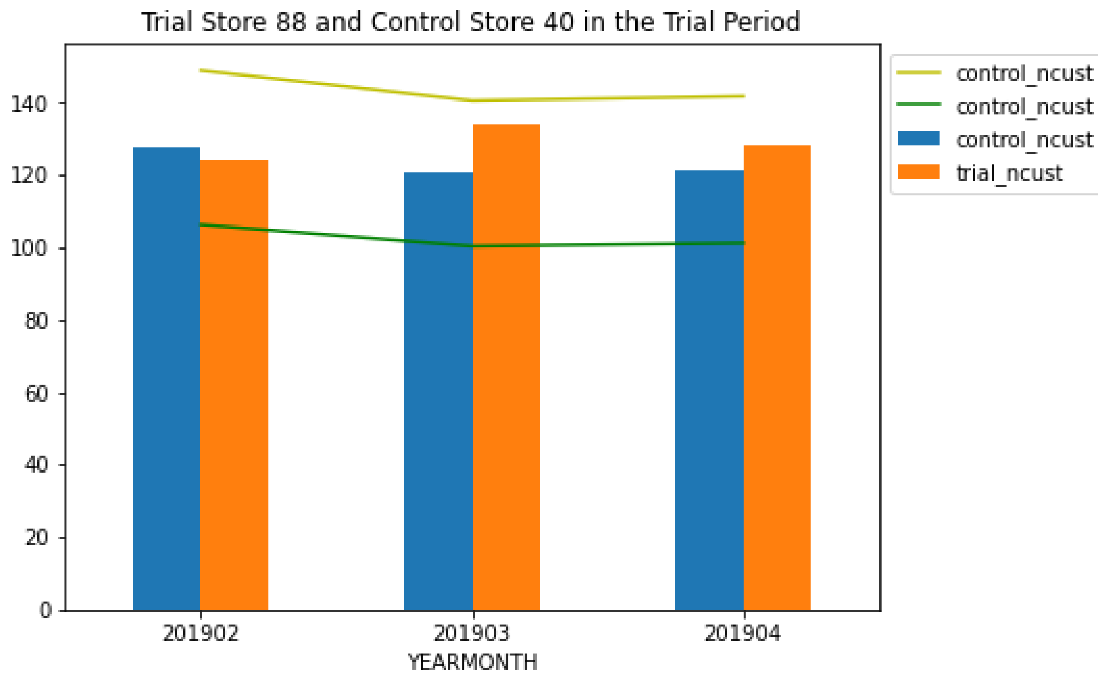
[89]:

```
# First do bar charts to focus on the trial period
storepair = [[77, 233], [86, 155], [88, 40]]
for stores in storepair: # stores numbers are stored as [trial, control] in␣
↪storepair
    trial = stores[0]
    control = stores[1]
    plot_control = percentdiff[(percentdiff['CONTROL_NBR'] == control) &␣
↪(percentdiff.YEARMONTH >= 201902) & (percentdiff.YEARMONTH <= 201904)]\
                    [['YEARMONTH', 'CONTROL_NBR', 'scaled_n_cust_c']]
    plot_control = plot_control.rename(columns = {"CONTROL_NBR" : "STORE_NBR",␣
↪"scaled_n_cust_c": "control_ncust"})
    plot_trial = percentdiff[(percentdiff['TRIAL_NBR'] == trial) & (percentdiff.
↪YEARMONTH >= 201902) & (percentdiff.YEARMONTH <= 201904)]\
                    [['YEARMONTH', 'TRIAL_NBR', 'n_cust_t']]
    plot_trial = plot_trial.rename(columns = {"TRIAL_NBR" : "STORE_NBR",␣
↪"n_cust_t": "trial_ncust"})
    toplot = plot_control[["YEARMONTH", "control_ncust"]].
↪merge(plot_trial[["YEARMONTH", "trial_ncust"]],on="YEARMONTH").
↪set_index("YEARMONTH")
    ax = toplot.plot(kind = 'bar',  figsize=(7, 5))


    # plot the thresholds as lines
    std = percentdiff[(percentdiff['CONTROL_NBR'] == control) & (percentdiff.
↪YEARMONTH < 201902)]['cust_percent_diff'].std()
    threshold95 = plot_control.reset_index()[['YEARMONTH', 'control_ncust']]
    threshold95.control_ncust = threshold95.control_ncust*(1+std*2)
    threshold5 = plot_control.reset_index()[['YEARMONTH', 'control_ncust']]
    threshold5.control_ncust = threshold5.control_ncust*(1-std*2)
    ax95 = threshold95.plot.line(x = 'YEARMONTH', y =␣
↪'control_ncust',color='y', figsize=(7, 5), use_index=False, ax = ax)
    ax5 = threshold5.plot.line(x = 'YEARMONTH', y = 'control_ncust', color='g',␣
↪figsize=(7, 5), use_index=False, ax = ax)

    # Other plot features
    plt.legend(loc = "upper left",bbox_to_anchor=(1.0, 1.0))
    titlestr = 'Trial Store ' + str(trial) + ' and Control Store ' +␣
↪str(control) + ' in the Trial Period'
```

```
    ax.set_title(titlestr)
    plt.show()
```

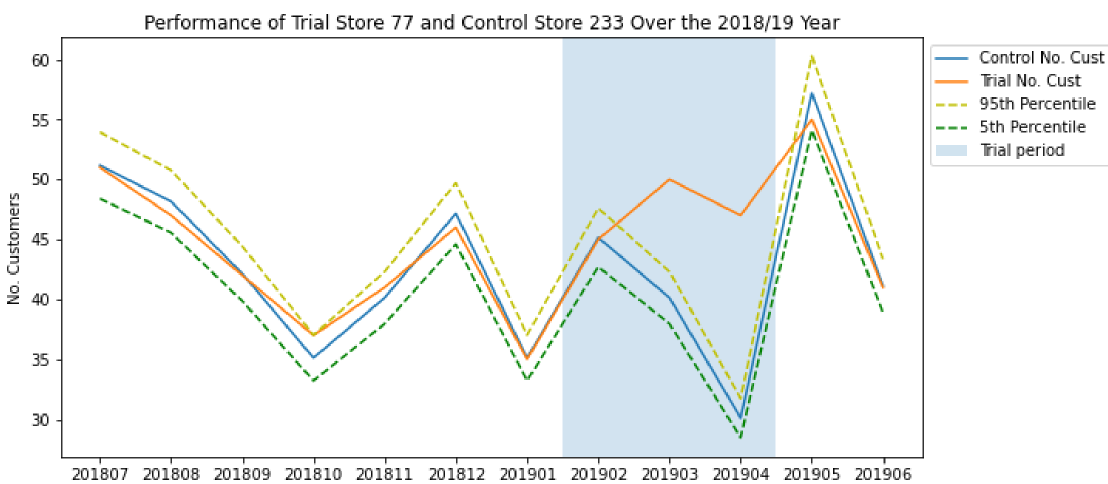


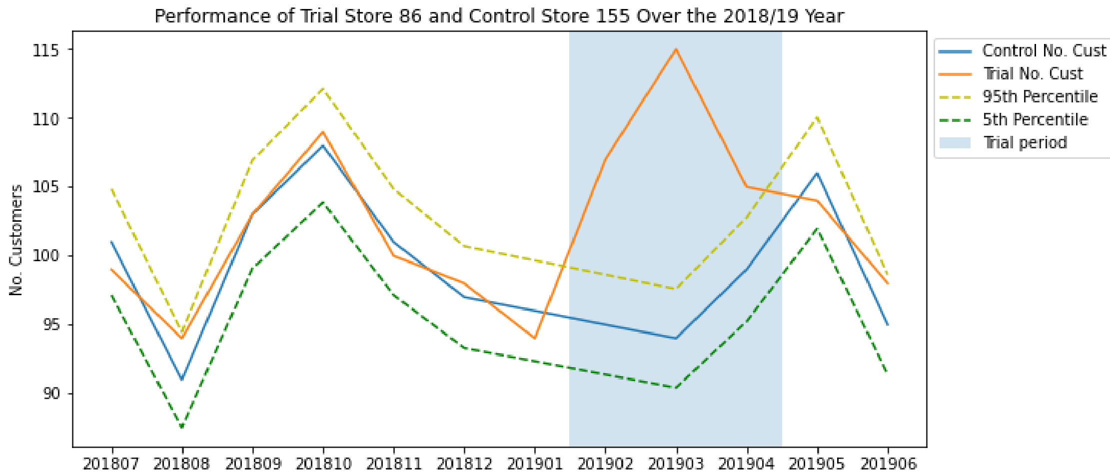


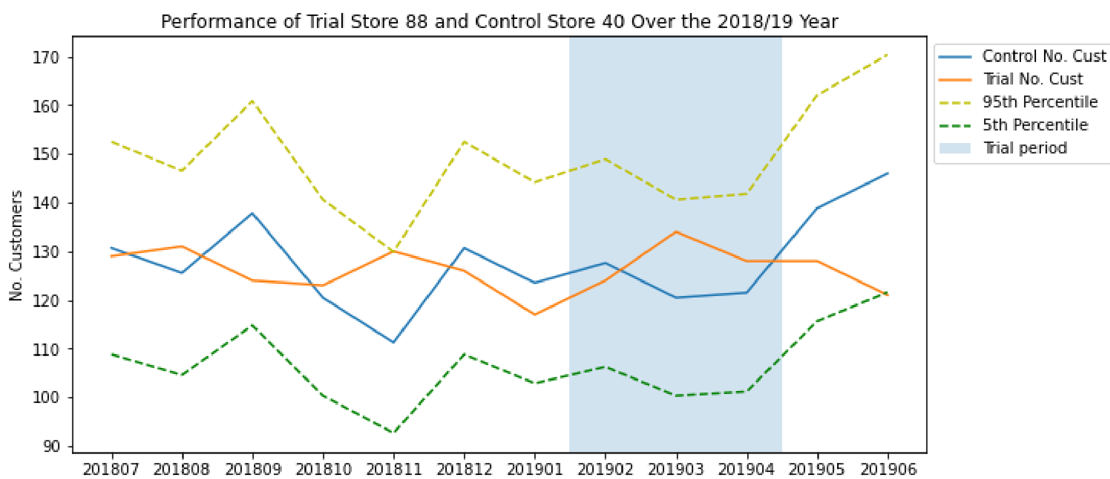


[88]:
```
# Then do line graphs to show a full year's trend
storepair = [[77, 233], [86, 155], [88, 40]]
for stores in storepair: # stores numbers are stored as [trial, control] in␣
↪storepair
    trial = stores[0]
    control = stores[1]
    plot_control = percentdiff[(percentdiff['CONTROL_NBR'] == control)]\
                    [['YEARMONTH', 'CONTROL_NBR', 'scaled_n_cust_c']]
    plot_control = plot_control.rename(columns = {"CONTROL_NBR" : "STORE_NBR",␣
↪"scaled_n_cust_c": "control_ncust"})
    plot_trial = percentdiff[(percentdiff['TRIAL_NBR'] == trial)]\
                    [['YEARMONTH', 'TRIAL_NBR', 'n_cust_t']]
    plot_trial = plot_trial.rename(columns = {"TRIAL_NBR" : "STORE_NBR",␣
↪"n_cust_t": "trial_ncust"})

    ax = plot_control.plot.line(x = "YEARMONTH", y = 'control_ncust',␣
↪use_index=False, label = 'Control No. Cust')
    ax_trial = plot_trial.plot.line(x = "YEARMONTH", y = 'trial_ncust',␣
↪use_index=False, ax=ax, label = 'Trial No. Cust')

    # plot the thresholds as lines
    std = percentdiff[(percentdiff['CONTROL_NBR'] == control) & (percentdiff.
↪YEARMONTH < 201902)]['cust_percent_diff'].std()
    threshold95 = plot_control.reset_index()[['YEARMONTH', 'control_ncust']]
```

```
    threshold95.control_ncust = threshold95.control_ncust*(1+std*2)
    threshold5 = plot_control.reset_index()[['YEARMONTH', 'control_ncust']]
    threshold5.control_ncust = threshold5.control_ncust*(1-std*2)
    ax95 = threshold95.plot.line(x = 'YEARMONTH', y =␣
↪'control_ncust',color='y', linestyle = '--', figsize=(10, 5),␣
↪use_index=False, ax = ax, label = '95th Percentile')
    ax5 = threshold5.plot.line(x = 'YEARMONTH', y = 'control_ncust', color='g',␣
↪ linestyle = '--', figsize=(10, 5), use_index=False, ax = ax, label = '5th␣
↪Percentile')
    ax.add_patch(Rectangle((6.5, 0), 3, 2000, alpha = 0.2, label = 'Trial␣
↪period'))

    # Other plot features
    ax.set_ylabel('No. Customers')
    plt.legend(loc = "upper left",bbox_to_anchor=(1.0, 1.0))
    titlestr = 'Performance of Trial Store ' + str(trial) + ' and Control Store␣
↪' + str(control) + ' Over the 2018/19 Year'
    positions = (0,1,2,3,4,5,6,7,8,9, 10, 11)
    labels = ("201807", '201808', '201809', '201810', '201811', '201812',␣
↪'201901', '201902', '201903', '201904', '201905', '201906')
    plt.xticks (positions, labels)
    ax.set_title(titlestr)
    plt.show()
```







It looks like the number of customers is significantly higher in all of the three months for store 77 and 86. This seems to suggest that the trial had a significant impact on increasing the number of customers in trial store 86 but as we saw, the statistical significance in the total sales were not as large, compared to store 77. We should check with the Category Manager if there were special deals in the trial store that were may have resulted in lower prices, impacting the results. Likewise to when considering the total sales, there appears to be no significant different in the number of customers between the control and trial stores for store 88 over the trial period.

1.1 Conclusions

In this task, we found that the results for trial stores 77 and 86 showed a statistically significant difference in at least two stores of the three months of the trial period. However, this was not the case for store 88. We can check to see if the trial was implemented differently in store 88 but even so, we have been able to see that the trial has resulted in a significant increase in sales.

[ ]:

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