Quantium Virtual Internship - Task 2

February 21, 2024

1 Quantium Virtual Internship - Task 2

We need to evaluate the performance of a store trial that occured in stores 77, 86 and 88.

To do this, we will choose control store whose performance we will compare to the trial stores to see if there are significant inreases in store performance.

[ ]:
```python
# Load packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import scipy.stats as sp
import seaborn as sns

# Load data
qvi_data = pd.read_csv('data/QVI_data.csv')
qvi_data.head()
```

[ ]:
```
   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

                               PROD_NAME  PROD_QTY  TOT_SALES  PACK_SIZE  \
0  Natural Chip        Compny SeaSalt175g         2        6.0        175
1   Red Rock Deli Chikn&Garlic Aioli 150g         1        2.7        150
2   Grain Waves Sour    Cream&Chives 210G         1        3.6        210
3  Natural ChipCo      Hony Soy Chckn175g         1        3.0        175
4          WW Original Stacked Chips 160g         1        1.9        160

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

1.1 Calculating Monthly Measures

To select the control stores, we will compute monthly statistics for each store and choose control stores to be those whose statistics correlates best with each of the trial stores.

First, we compute a variety of monthly store metrics.

[ ]:
```python
# Measure calculations to be used during analysis

qvi_data['MONTH'] = pd.PeriodIndex(qvi_data['DATE'], freq='M').to_timestamp()

columns = ['MONTH', 'STORE_NBR', 'LYLTY_CARD_NBR', 'PROD_QTY', 'TOT_SALES']

# Total sales
monthly_sales = qvi_data[columns].groupby(columns[:2])['TOT_SALES'].sum().
↪reset_index()

# Number of customers
monthly_cnt = qvi_data[columns].groupby(columns[:2])['LYLTY_CARD_NBR'].count().
↪reset_index()
monthly_cnt.rename(columns={'LYLTY_CARD_NBR':'NUM_CUSTS'}, inplace=True)

# Average transactions per customer
monthly_cust_avg = qvi_data[columns].groupby(columns[:3])['PROD_QTY'].count().
↪groupby(columns[:2]).mean().reset_index()
monthly_cust_avg.rename(columns={'PROD_QTY':'AVG_TRNS'}, inplace=True)

# Average number of packets bought per customer
monthly_chips_avg = qvi_data[columns].groupby(columns[:3])['PROD_QTY'].sum().
↪groupby(columns[:2]).mean().reset_index()
monthly_chips_avg.rename(columns={'PROD_QTY':'AVG_CHIPS'})

# Average price per unit
qvi_data['PRICE_PER_UNIT'] = qvi_data['TOT_SALES'] / qvi_data['PROD_QTY']
monthly_ppu = qvi_data.groupby(columns[:2])['PRICE_PER_UNIT'].mean().
↪reset_index()
monthly_ppu.rename(columns={"PRICE_PER_UNIT":"AVG_PPU"})

to_merge = [monthly_sales, monthly_cnt, monthly_cust_avg, monthly_chips_avg,␣
↪monthly_ppu]
monthly_data = monthly_sales
for df in to_merge[1:]:
    monthly_data = monthly_data.merge(df, on=columns[:2])

monthly_data.head()
```

We will only consider stores with full observation periods. Then, we further filter out data from the pre-trial period, which will be used to determine the control stores.

```
[ ]: has_full_obs = monthly_data.groupby('STORE_NBR')['MONTH'].count() == 12
stores_with_full_obs = [store for store in has_full_obs.index if␣
 ↪has_full_obs[store]]

pretrial_df = monthly_data[(monthly_data['STORE_NBR'].
 ↪isin(stores_with_full_obs)) & (monthly_data['MONTH'] < '2019-02-01')]
pretrial_df.head()
```

```
[ ]:        MONTH  STORE_NBR  TOT_SALES  NUM_CUSTS  AVG_TRNS  PROD_QTY  \
0 2018-07-01          1      206.9         52  1.061224  1.265306
1 2018-07-01          2      150.8         41  1.051282  1.179487
2 2018-07-01          3     1205.7        138  1.232143  2.419643
3 2018-07-01          4     1399.9        160  1.250000  2.484375
4 2018-07-01          5      812.0        120  1.290323  2.580645

   PRICE_PER_UNIT
0        3.384615
1        3.239024
2        4.451449
3        4.405625
4        3.383333
```

1.2 Selecting Control Stores

We calculate both the Pearson correlation and magnitude distance between the trial stores and each other store.

```
[ ]: def store_correlation(monthly_data, metric_col, storeX, storeY):
    storeX_array = monthly_data[monthly_data['STORE_NBR'] == storeX][metric_col]
    storeY_array = monthly_data[monthly_data['STORE_NBR'] == storeY][metric_col]
    return sp.pearsonr(storeX_array, storeY_array)[0]

def calculate_correlation_table(pretrial_df, trial_store):
    corr_df = pd.DataFrame()
    corr_df['Control'] = pretrial_df['STORE_NBR'].unique()
    corr_df['Trial Store'] = trial_store

    for metric in pretrial_df.columns[2:]:
        if metric != "AVG_TRNS":
            col_name = metric + '_COR'
            corr_df[col_name] = corr_df['Control'].apply(lambda x :␣
 ↪store_correlation(pretrial_df, metric, x, trial_store))

    return corr_df

trial_stores = [77, 86, 88]
```

```
correlation_table = pd.concat([calculate_correlation_table(pretrial_df,␣
↪trial_store) for trial_store in trial_stores])

# Remove rows where control is a trial store
correlation_table = correlation_table[~correlation_table['Control'].
↪isin(trial_stores)]

correlation_table.head()
```

[ ]:

```
   Control  Trial Store  TOT_SALES_COR  NUM_CUSTS_COR  PROD_QTY_COR  \
0        1           77       0.075218       0.355839     -0.791857
1        2           77      -0.263079      -0.379313     -0.034676
2        3           77       0.806644       0.861748      0.316541
3        4           77      -0.263300      -0.181233     -0.146667
4        5           77      -0.110652       0.434760      0.318414

   PRICE_PER_UNIT_COR
0           -0.851944
1            0.178421
2           -0.089079
3           -0.412672
4            0.136721
```

[ ]:

```
def calculate_dist(pretrial_df, metric_col, storeX, storeY):
    arrayX = np.array(monthly_data[monthly_data['STORE_NBR'] ==␣
↪storeX][metric_col])
    arrayY = np.array(monthly_data[monthly_data['STORE_NBR'] ==␣
↪storeY][metric_col])
    dist = np.abs(arrayX - arrayY)
    return np.mean(1 - (dist - np.min(dist))/(np.max(dist) - np.min(dist)))
    #return 1 - (np.mean(dist) - np.min(dist)) / (np.max(dist) - np.min(dist))

def calculate_dist_table(pretrial_df, trial_store):
    dist_df = pd.DataFrame()
    dist_df['Control'] = pretrial_df['STORE_NBR'].unique()
    dist_df['Trial Store'] = trial_store
    for metric in pretrial_df.columns[2:]:
        col_name = metric + '_DIST'
        dist_df[col_name] = dist_df['Control'].apply(lambda x :␣
↪calculate_dist(pretrial_df, metric, x, trial_store))

    return dist_df

trial_stores = [77, 86, 88]
dist_table = pd.concat([calculate_dist_table(pretrial_df, trial_store) for␣
↪trial_store in trial_stores])
```

```
# Remove rows where control is a trial store
dist_table = dist_table[~dist_table['Control'].isin(trial_stores)]

dist_table.head()
```

[ ]:

```
   Control  Trial Store  TOT_SALES_DIST  NUM_CUSTS_DIST  AVG_TRNS_DIST  \
0        1           77        0.343210        0.725490       0.653718
1        2           77        0.547271        0.517857       0.749035
2        3           77        0.487141        0.492188       0.537680
3        4           77        0.525581        0.501157       0.440281
4        5           77        0.494214        0.430233       0.319630

   PROD_QTY_DIST  PRICE_PER_UNIT_DIST
0       0.568265             0.517284
1       0.487811             0.552543
2       0.480010             0.530014
3       0.678465             0.540804
4       0.489252             0.591946
```

[ ]:

```
# Merge correlation and distance tables and use average of scores to get final␣
↪score for the control
metrics = ['TOT_SALES', 'NUM_CUSTS']

comparison_df = correlation_table[['Control', 'Trial Store','TOT_SALES_COR',␣
↪'NUM_CUSTS_COR']].merge(
    dist_table[['Control', 'Trial Store','TOT_SALES_DIST', 'NUM_CUSTS_DIST']],
    on = ['Control', 'Trial Store']
)

comparison_df['Score'] = comparison_df.iloc[:, 2:6].mean(axis=1)

comparison_df.head()
```

[ ]:

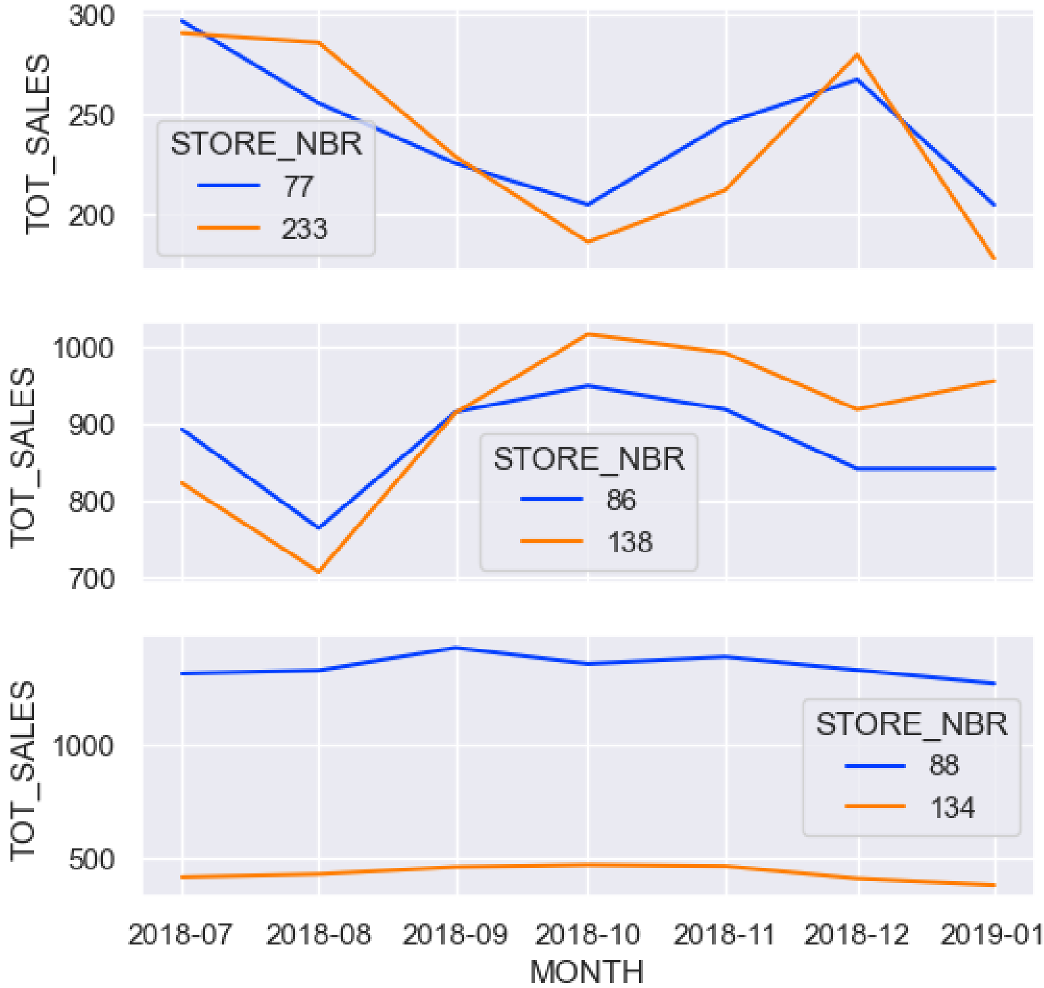
```
   Control  Trial Store  TOT_SALES_COR  NUM_CUSTS_COR  TOT_SALES_DIST  \
0        1           77       0.075218       0.355839        0.343210
1        2           77      -0.263079      -0.379313        0.547271
2        3           77       0.806644       0.861748        0.487141
3        4           77      -0.263300      -0.181233        0.525581
4        5           77      -0.110652       0.434760        0.494214

   NUM_CUSTS_DIST     Score
0        0.725490  0.374939
1        0.517857  0.105684
```

```
2         0.492188  0.661930
3         0.501157  0.145552
4         0.430233  0.312139
```

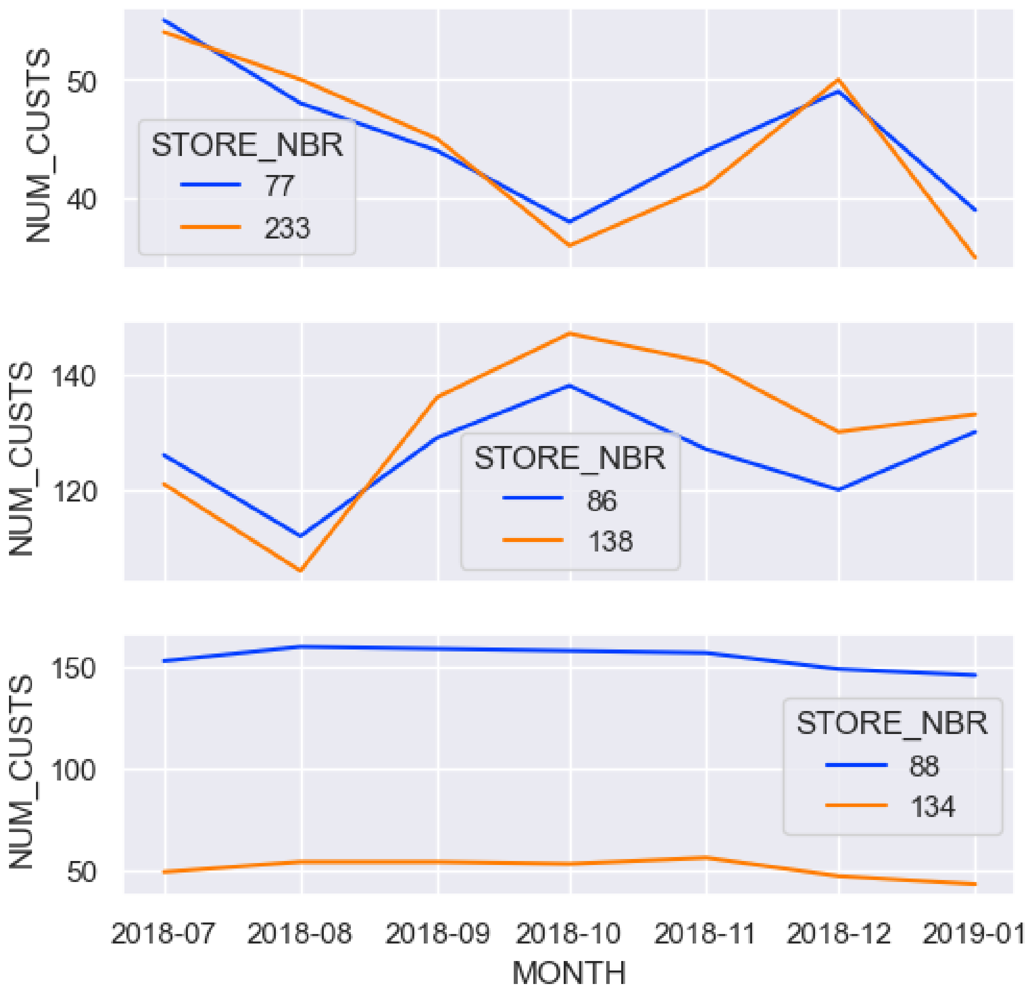
[ ]:
```
max_scores = comparison_df.groupby('Trial Store')['Score'].max().reset_index()
controls = max_scores.merge(comparison_df[['Control', 'Score']], how='inner',␣
↪on='Score')

controls
```

[ ]:
```
   Trial Store     Score  Control
0           77  0.830999      233
1           86  0.770207      138
2           88  0.790257      134
```

[ ]:
```
sns.set_theme()

comps = [[77,233], [86, 138], [88, 134]]

def plot_controls(metric):
    fig, ax = plt.subplots(3, 1, figsize=(6,6), sharex=True)

    for i in range(3):
        sns.lineplot(
            data = pretrial_df[pretrial_df['STORE_NBR'].isin(comps[i])],
            x='MONTH', y=metric,
            hue='STORE_NBR',
            palette='bright',
            ax=ax[i]
        )
plot_controls('TOT_SALES')
```




```
[ ]: plot_controls('NUM_CUSTS')
```



Indeed there appears to be a strong correlation between the control stores and trial stores.

1.3 Trial Assessment

[ ]:
```
trial_store1, trial_store2, trial_store3 = 77, 86, 88
control_store1, control_store2, control_store3 = 233, 138, 134
```

To account for differences between the trial store and its control, we will scale the control measures to match the trial store.

We then calculate the percentage difference and calculate a t-score to tell us if there is a statistically significant increase during the trial months.

Since there are 8 months in the pre-trial period, the number of degrees of freedom is 8-1=7.

[ ]:
```
def compare_tot_sales(trial_store, control_store):
    scaling_factor = pretrial_df[pretrial_df['STORE_NBR'] ==␣
↪trial_store]['TOT_SALES'].sum() / \
```

```
        pretrial_df[pretrial_df['STORE_NBR'] == control_store]['TOT_SALES'].
↪sum()

    trial_store_sales = monthly_data[monthly_data['STORE_NBR'] ==␣
↪trial_store][['MONTH','TOT_SALES']].rename(columns={'TOT_SALES':
↪'trial_sales'})
    control_sales = monthly_data[monthly_data['STORE_NBR'] ==␣
↪control_store][['MONTH','TOT_SALES']].rename(columns={'TOT_SALES':
↪'control_sales'})
    trial_store_sales = trial_store_sales.merge(control_sales, on='MONTH')
    trial_store_sales['scaled_control_sales'] = scaling_factor *␣
↪trial_store_sales['control_sales']
    trial_store_sales['percentage_diff'] =␣
↪100*(trial_store_sales['trial_sales'] -␣
↪trial_store_sales['scaled_control_sales'])/
↪trial_store_sales['scaled_control_sales']

    std_dev = np.std(trial_store_sales[trial_store_sales['MONTH'] <␣
↪'2019-02-01']['percentage_diff'])
    trial_store_sales['t_value'] = (trial_store_sales['percentage_diff'] - np.
↪mean(trial_store_sales['percentage_diff'])) / std_dev

    return trial_store_sales

trial_store_sales = compare_tot_sales(trial_store1, control_store1)
trial_store_sales
```

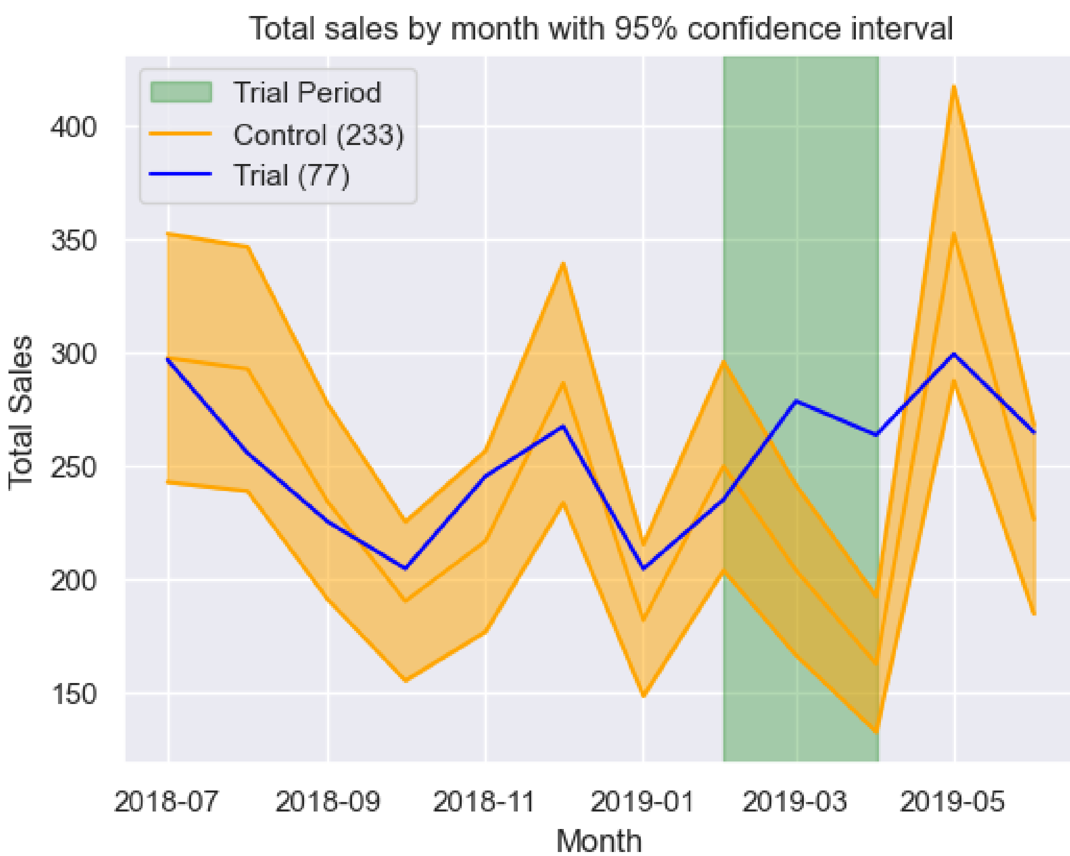
[ ]:

```
         MONTH  trial_sales  control_sales  scaled_control_sales  \
0   2018-07-01        296.8          290.7            297.565550
1   2018-08-01        255.5          285.9            292.652187
2   2018-09-01        225.2          228.6            233.998916
3   2018-10-01        204.5          185.7            190.085733
4   2018-11-01        245.3          211.6            216.597421
5   2018-12-01        267.3          279.8            286.408121
6   2019-01-01        204.4          177.5            181.692071
7   2019-02-01        235.0          244.0            249.762622
8   2019-03-01        278.5          199.1            203.802205
9   2019-04-01        263.5          158.6            162.345704
10  2019-05-01        299.3          344.4            352.533799
11  2019-06-01        264.7          221.0            226.219424

    percentage_diff   t_value
0         -0.257271 -0.976103
1        -12.694997 -2.325110
2         -3.760238 -1.356038
3          7.583035 -0.125737
```

```
4          13.251579  0.489078
5          -6.671641 -1.671812
6          12.498029  0.407347
7          -5.910661 -1.589275
8          36.652103  3.027119
9          62.307960  5.809776
10        -15.100339 -2.585995
11         17.010288  0.896751
```

[ ]:
```
def graph_tot_sales(trial_store_sales, trial_store, control_store):
    std_dev = np.std(trial_store_sales[trial_store_sales['MONTH'] <␣
↪'2019-02-01']['percentage_diff'])
    trial_store_sales['percentile_95'] =␣
↪trial_store_sales['scaled_control_sales']*(1 + 2*std_dev/100)
    trial_store_sales['percentile_05'] =␣
↪trial_store_sales['scaled_control_sales']*(1 - 2*std_dev/100)

    fig, ax = plt.subplots()

    ax.axvspan(xmin = pd.to_datetime('2019-02-01'),
            xmax = pd.to_datetime('2019-04-01'),
            ymin = 0,
            ymax = 1,
            color='green',
            alpha=0.3,
            label="Trial Period"
    )
    sns.lineplot(
        data = trial_store_sales,
        x = 'MONTH', y='scaled_control_sales',
        label = "Control (" + str(control_store) + ")",
        color='orange'
    )
    sns.lineplot(
        data = trial_store_sales,
        x = 'MONTH', y='percentile_95',
        color='orange'
    )
    pc5 = sns.lineplot(
        data = trial_store_sales,
        x = 'MONTH', y='percentile_05',
        color='orange'
    )
```

```
    sns.lineplot(
        data = trial_store_sales,
        x = 'MONTH', y='trial_sales',
        label = "Trial (" + str(trial_store) + ")",
        color='blue'
    )

    line = pc5.get_lines()
    plt.fill_between(line[0].get_xdata(), line[1].get_ydata(), line[2].
 ↪get_ydata(), color='orange', alpha=.5)

    ax.set_ylabel("Total Sales")
    ax.set_xlabel("Month")
    ax.set_title("Total sales by month with 95% confidence interval")

graph_tot_sales(trial_store_sales, trial_store1, control_store1)
```



Now we will do the same with the number of customers, to see if this increased significantly during the trial period.

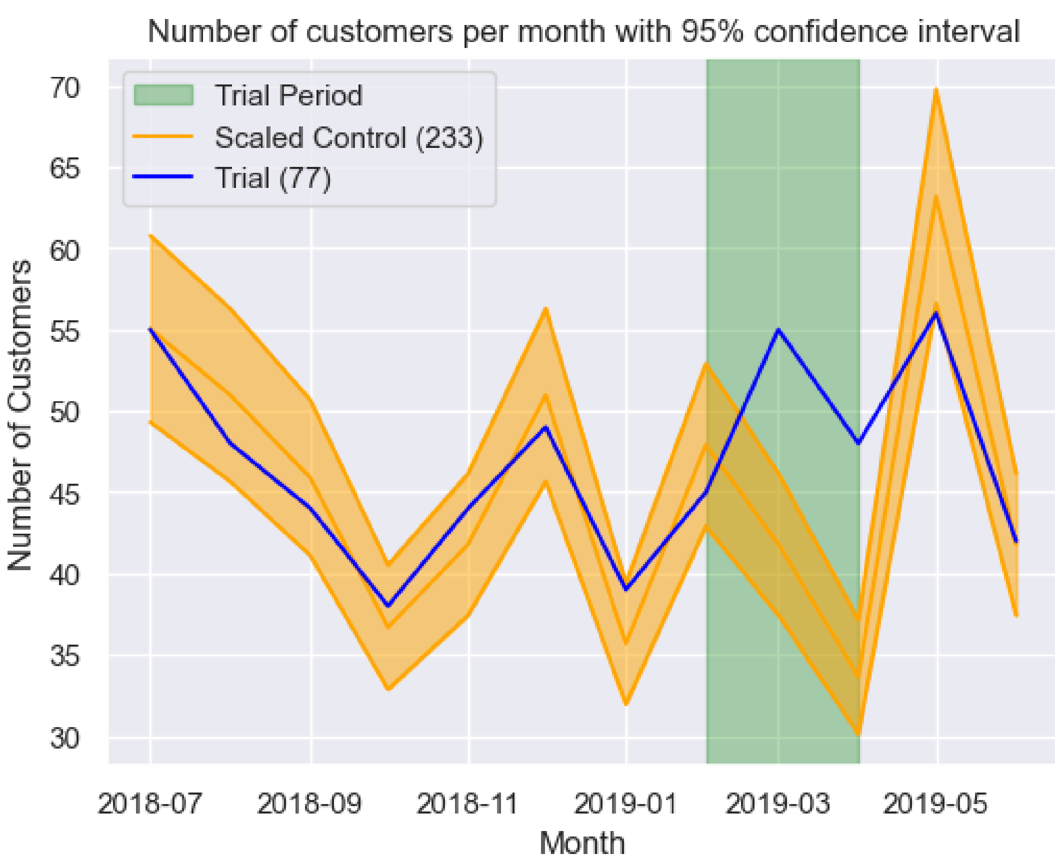
```
[ ]: def compare_num_custs(trial_store, control_store):
        scaling_factor = pretrial_df[pretrial_df['STORE_NBR'] ==␣
     ↪trial_store]['NUM_CUSTS'].sum() / \
            pretrial_df[pretrial_df['STORE_NBR'] == control_store]['NUM_CUSTS'].
     ↪sum()

        trial_num_custs = monthly_data[monthly_data['STORE_NBR'] ==␣
     ↪trial_store][['MONTH','NUM_CUSTS']].rename(columns={'NUM_CUSTS':
     ↪'trial_num_custs'})
        control_num_custs = monthly_data[monthly_data['STORE_NBR'] ==␣
     ↪control_store][['MONTH','NUM_CUSTS']].rename(columns={'NUM_CUSTS':
     ↪'control_num_custs'})
        trial_num_custs = trial_num_custs.merge(control_num_custs, on='MONTH')
        trial_num_custs['scaled_control_num_custs'] = scaling_factor *␣
     ↪trial_num_custs['control_num_custs']
        trial_num_custs['percentage_diff'] =␣
     ↪100*(trial_num_custs['trial_num_custs'] -␣
     ↪trial_num_custs['scaled_control_num_custs'])/
     ↪trial_num_custs['scaled_control_num_custs']

        std_dev = np.std(trial_num_custs[trial_num_custs['MONTH'] <␣
     ↪'2019-02-01']['percentage_diff'])
        trial_num_custs['t_value'] = (trial_num_custs['percentage_diff'] - np.
     ↪mean(trial_num_custs['percentage_diff'])) / std_dev

        return trial_num_custs

    trial_num_custs = compare_num_custs(trial_store1, control_store1)
    trial_num_custs
```

```
[ ]:        MONTH  trial_num_custs  control_num_custs  scaled_control_num_custs  \
     0  2018-07-01               55                 54                 55.041801
     1  2018-08-01               48                 50                 50.964630
     2  2018-09-01               44                 45                 45.868167
     3  2018-10-01               38                 36                 36.694534
     4  2018-11-01               44                 41                 41.790997
     5  2018-12-01               49                 50                 50.964630
     6  2019-01-01               39                 35                 35.675241
     7  2019-02-01               45                 47                 47.906752
     8  2019-03-01               55                 41                 41.790997
     9  2019-04-01               48                 33                 33.636656
     10 2019-05-01               56                 62                 63.196141
     11 2019-06-01               42                 41                 41.790997

         percentage_diff   t_value
     0         -0.075943 -1.001300
```

```
1          -5.817035 -2.103119
2          -4.072906 -1.768389
3           3.557659 -0.303945
4           5.285835  0.027723
5          -3.854890 -1.726548
6           9.319513  0.801859
7          -6.067521 -2.151192
8          31.607294  5.079289
9          42.701463  7.208461
10        -11.386995 -3.172096
11          0.500115 -0.890743
```

[ ]:
```python
def graph_num_custs(trial_num_custs, trial_store, control_store):
    std_dev = np.std(trial_num_custs[trial_num_custs['MONTH'] <␣
 ↪'2019-02-01']['percentage_diff'])
    trial_num_custs['percentile_95'] =␣
 ↪trial_num_custs['scaled_control_num_custs']*(1 + 2*std_dev/100)
    trial_num_custs['percentile_05'] =␣
 ↪trial_num_custs['scaled_control_num_custs']*(1 - 2*std_dev/100)

    fig, ax = plt.subplots()

    ax.axvspan(xmin = pd.to_datetime('2019-02-01'),
            xmax = pd.to_datetime('2019-04-01'),
            ymin = 0,
            ymax = 1,
            color='green',
            alpha=0.3,
            label="Trial Period"
    )
    sns.lineplot(
        data = trial_num_custs,
        x = 'MONTH', y='scaled_control_num_custs',
        label = "Scaled Control (" + str(control_store) + ")",
        color='orange'
    )
    sns.lineplot(
        data = trial_num_custs,
        x = 'MONTH', y='percentile_95',
        color='orange'
    )
    pc5 = sns.lineplot(
        data = trial_num_custs,
```

```
        x = 'MONTH', y='percentile_05',
        color='orange'
    )
    sns.lineplot(
        data = trial_num_custs,
        x = 'MONTH', y='trial_num_custs',
        label = "Trial (" + str(trial_store) + ")",
        color='blue'
    )

    line = pc5.get_lines()
    plt.fill_between(line[0].get_xdata(), line[1].get_ydata(), line[2].
↪get_ydata(), color='orange', alpha=.5)

    ax.set_ylabel("Number of Customers")
    ax.set_xlabel("Month")
    ax.set_title("Number of customers per month with 95% confidence interval")

graph_num_custs(trial_num_custs, trial_store1, control_store1)
```



Now we want to perform the same procedure for the other two trial stores and their control.

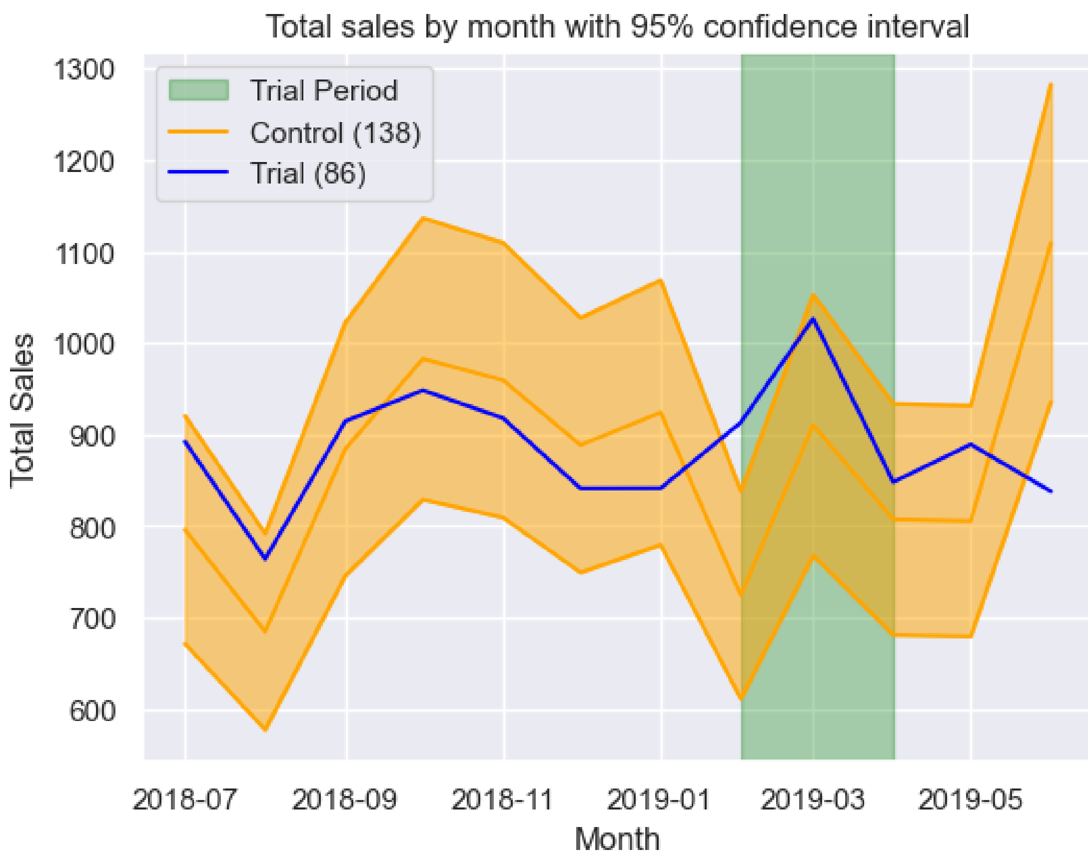
[ ]:
```
trial_store_sales2 = compare_tot_sales(trial_store2, control_store2)

trial_store_sales2
```

[ ]:
```
         MONTH  trial_sales  control_sales  scaled_control_sales  \
0   2018-07-01       892.20          822.4            795.977327
1   2018-08-01       764.05          707.4            684.672132
2   2018-09-01       914.60          913.6            884.247186
3   2018-10-01       948.40         1015.4            982.776481
4   2018-11-01       918.00          991.4            959.547571
5   2018-12-01       841.20          918.0            888.505820
6   2019-01-01       841.40          954.8            924.123483
7   2019-02-01       913.20          748.6            724.548428
8   2019-03-01      1026.80          940.6            910.379711
9   2019-04-01       848.20          834.2            807.398208
10  2019-05-01       889.30          832.4            805.656040
11  2019-06-01       838.00         1146.0           1109.180468

    percentage_diff   t_value
0         12.088620  1.174582
1         11.593559  1.111285
2          3.432616  0.067850
3         -3.497894 -0.818265
4         -4.329913 -0.924644
5         -5.324199 -1.051771
6         -8.951562 -1.515555
7         26.037124  2.957997
8         12.788102  1.264016
9          5.053491  0.275091
10        10.382093  0.956390
11       -24.448724 -3.496977
```

The t-value is too low for the trial performance to be significantly greater than the trial performance.

We can also see this in the following visual:

[ ]:
```
graph_tot_sales(trial_store_sales2, trial_store2, control_store2)
```



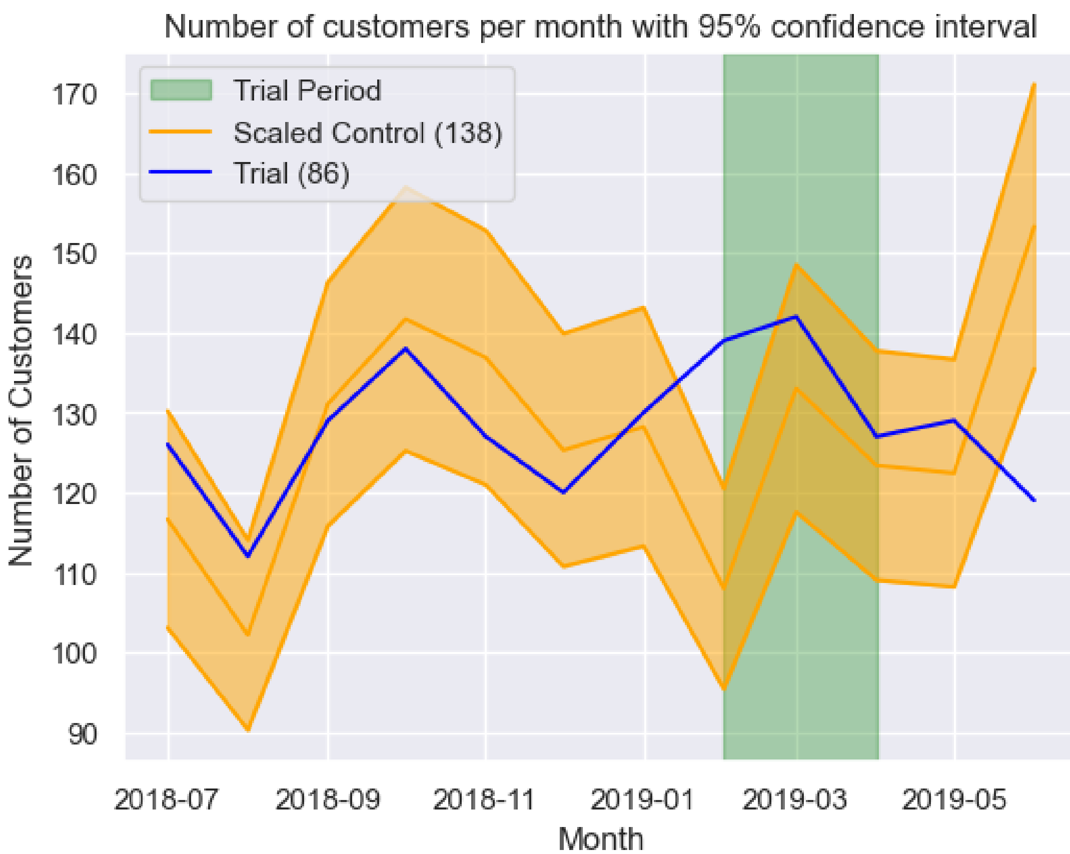
Looking now at the number of customers:

```
[ ]: trial_num_custs2 = compare_num_custs(trial_store2, control_store2)
     trial_num_custs2
```

```
[ ]:         MONTH  trial_num_custs  control_num_custs  scaled_control_num_custs  \
     0   2018-07-01              126                121                116.636066
     1   2018-08-01              112                106                102.177049
     2   2018-09-01              129                136                131.095082
     3   2018-10-01              138                147                141.698361
     4   2018-11-01              127                142                136.878689
     5   2018-12-01              120                130                125.311475
     6   2019-01-01              130                133                128.203279
     7   2019-02-01              139                112                107.960656
     8   2019-03-01              142                138                133.022951
     9   2019-04-01              127                128                123.383607
     10  2019-05-01              129                127                122.419672
     11  2019-06-01              119                159                153.265574

         percentage_diff   t_value
```

```
0         8.028335  1.024978
1         9.613657  1.297645
2        -1.598139 -0.630729
3        -2.610024 -0.804768
4        -7.217112 -1.597164
5        -4.238619 -1.084878
6         1.401463 -0.114812
7        28.750607  4.589107
8         6.748497  0.804852
9         2.931016  0.148264
10        5.375221  0.568655
11      -22.356993 -4.201150
```

[ ]:
```
graph_num_custs(trial_num_custs2, trial_store2, control_store2)
```



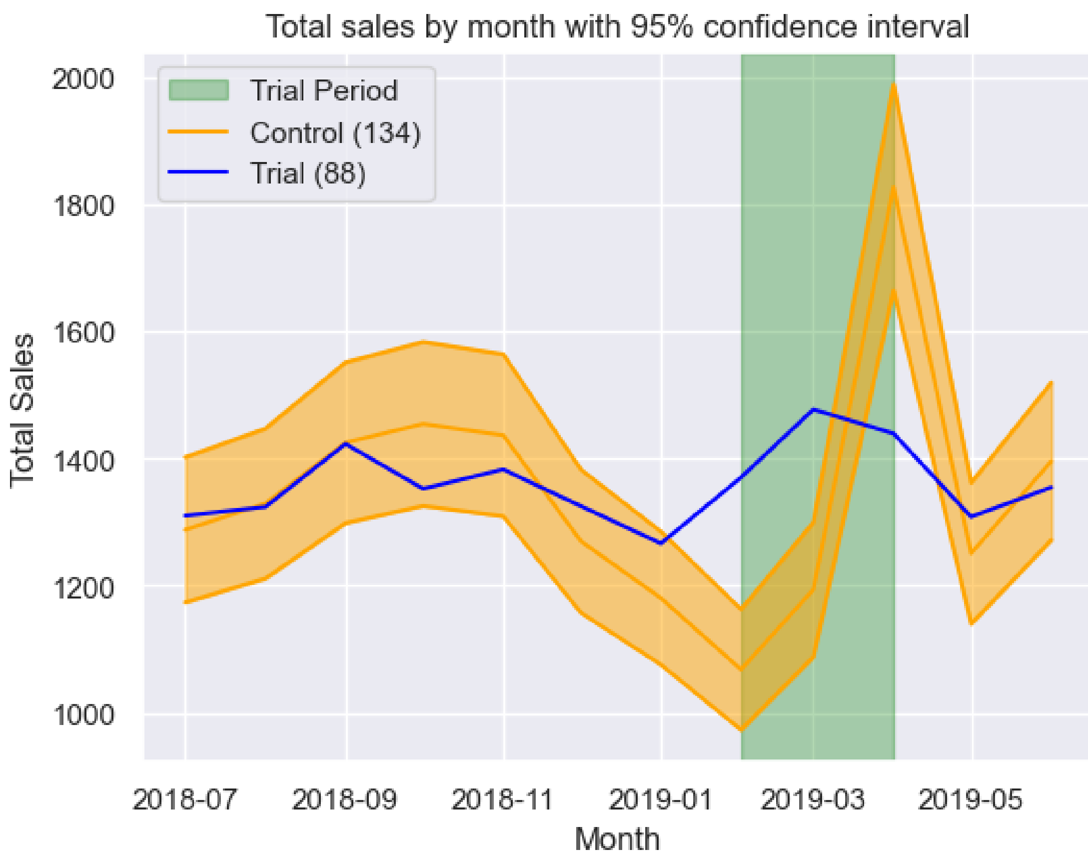
So the number of customers does not significantly increase for two out of three months of the trial period.

Let's consider the final trial store.

```
[ ]: trial_store_sales3 = compare_tot_sales(trial_store3, control_store3)
     trial_store_sales3
```

```
[ ]:         MONTH  trial_sales  control_sales  scaled_control_sales  \
     0  2018-07-01      1310.00         419.20           1287.911965
     1  2018-08-01      1323.80         432.65           1329.234522
     2  2018-09-01      1423.00         463.80           1424.936950
     3  2018-10-01      1352.40         473.40           1454.431117
     4  2018-11-01      1382.80         467.60           1436.611725
     5  2018-12-01      1325.20         413.40           1270.092573
     6  2019-01-01      1266.40         384.20           1180.381148
     7  2019-02-01      1370.20         347.60           1067.934635
     8  2019-03-01      1477.20         388.60           1193.899308
     9  2019-04-01      1439.40         594.60           1826.794977
     10 2019-05-01      1308.25         407.10           1250.737025
     11 2019-06-01      1354.60         454.20           1395.442783

         percentage_diff   t_value
     0          1.715027 -0.262155
     1         -0.408846 -0.741000
     2         -0.135932 -0.679469
     3         -7.015191 -2.230455
     4         -3.745739 -1.493330
     5          4.338851  0.329408
     6          7.287379  0.994178
     7         28.303733  5.732490
     8         23.729027  4.701084
     9        -21.206265 -5.429951
     10         4.598327  0.387909
     11        -2.926869 -1.308709
```

```
[ ]: graph_tot_sales(trial_store_sales3, trial_store3, control_store3)
```



So there is a statistically significant increase for two out of the three months (but a signifant decrease in the third month).

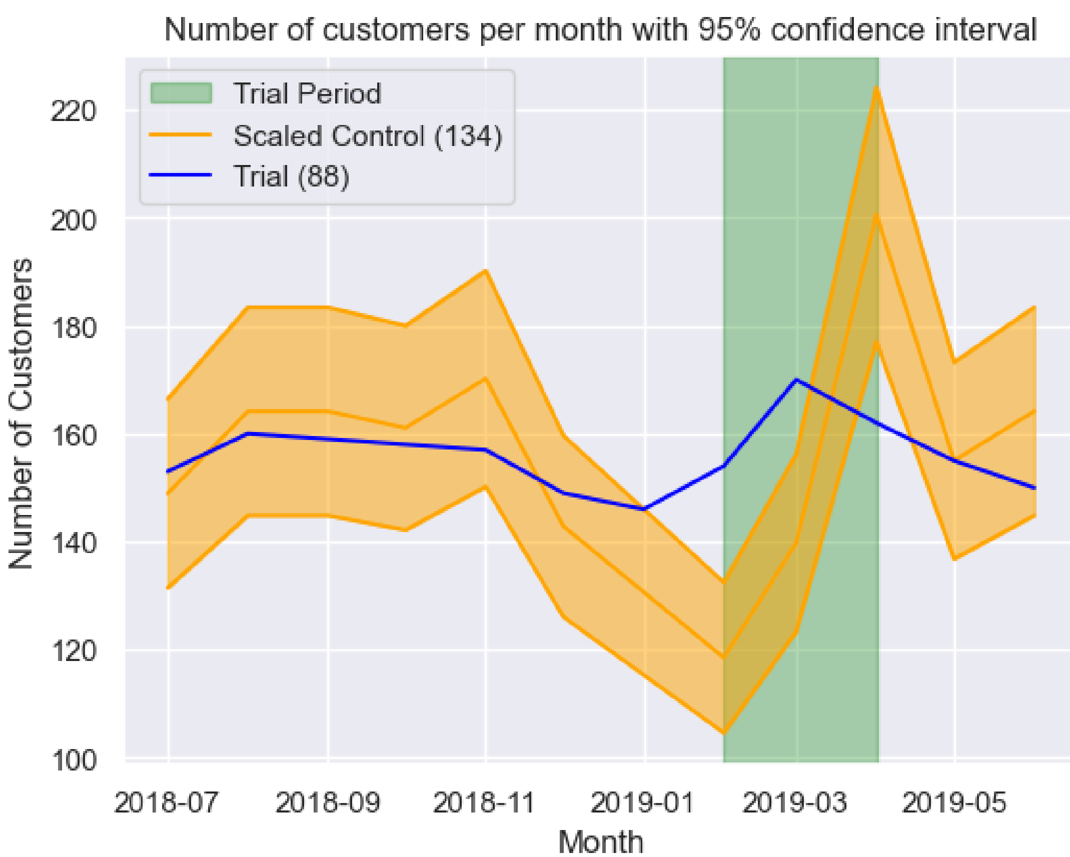
[ ]:
```
trial_num_custs3 = compare_num_custs(88, 134)
trial_num_custs3
```

[ ]:

	MONTH	trial_num_custs	control_num_custs	scaled_control_num_custs	\
0	2018-07-01	153	49	148.926966	
1	2018-08-01	160	54	164.123596	
2	2018-09-01	159	54	164.123596	
3	2018-10-01	158	53	161.084270	
4	2018-11-01	157	56	170.202247	
5	2018-12-01	149	47	142.848315	
6	2019-01-01	146	43	130.691011	
7	2019-02-01	154	39	118.533708	
8	2019-03-01	170	46	139.808989	
9	2019-04-01	162	66	200.595506	
10	2019-05-01	155	51	155.005618	
11	2019-06-01	150	54	164.123596	

```
    percentage_diff   t_value
0          0.027349  0.080935
1         -0.025125 -0.812569
2         -0.031218 -0.916317
3         -0.019147 -0.710779
4         -0.077568 -1.705544
5          0.043064  0.348526
6          0.117139  1.609828
7          0.299208  4.710020
8          0.215945  3.292246
9         -0.192405 -3.660925
10        -0.000036 -0.385371
11        -0.086055 -1.850050
```

[ ]:
```
graph_num_custs(trial_num_custs3, trial_store3, control_store3)
```



1.4 Conclusion

We've found control store 233, 138, and 134 for the trial stores 77, 86, and 88, respectively.

Comparing the trial stores to the compare stores revealed a statistically significant increase in both total sales and number of customers in two out of three months of the trial for stores 77 and 88. The same is not true for store 86, so we should ask the client if there was anything different aboutt the implementation of this trial.

Overall, the trial gave a significant increase in sales.