tom-dove-task-2

February 20, 2024

1 Quantium Virtual Internship - Retail Strategy and Analytics - 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.

[ ]:
```
# 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
```

[ ]:
```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	PRICE_PER_UNIT
0	2018-07-01	1	206.9	52	1.061224	1.265306	3.384615
1	2018-07-01	2	150.8	41	1.051282	1.179487	3.239024
2	2018-07-01	3	1205.7	138	1.232143	2.419643	4.451449
3	2018-07-01	4	1399.9	160	1.250000	2.484375	4.405625
4	2018-07-01	5	812.0	120	1.290323	2.580645	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	PRICE_PER_UNIT_COR
0	1	77	0.075218	0.355839	-0.791857	-0.851944
1	2	77	-0.263079	-0.379313	-0.034676	0.178421
2	3	77	0.806644	0.861748	0.316541	-0.089079
3	4	77	-0.263300	-0.181233	-0.146667	-0.412672
4	5	77	-0.110652	0.434760	0.318414	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	PROD_QTY_DIST	PRICE_PER_UNIT_DIST
0	1	77	0.343210	0.725490	0.653718	0.568265	0.517284
1	2	77	0.547271	0.517857	0.749035	0.487811	0.552543
2	3	77	0.487141	0.492188	0.537680	0.480010	0.530014
3	4	77	0.525581	0.501157	0.440281	0.678465	0.540804
4	5	77	0.494214	0.430233	0.319630	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()
```

[ ]:

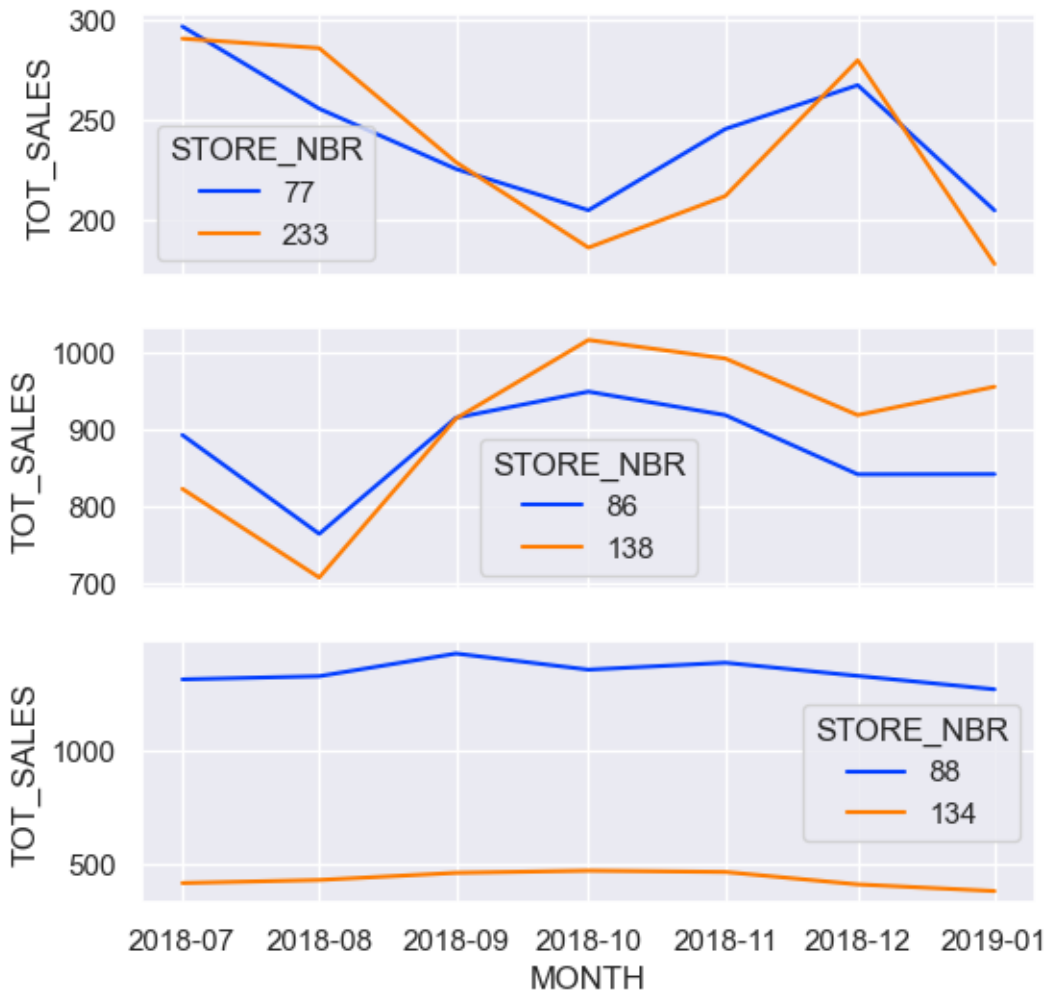
	Control	Trial Store	TOT_SALES_COR	NUM_CUSTS_COR	TOT_SALES_DIST	NUM_CUSTS_DIST	Score
0	1	77	0.075218	0.355839	0.343210	0.725490	0.374939
1	2	77	-0.263079	-0.379313	0.547271		
2	3	77	0.806644	0.861748	0.487141		
3	4	77	-0.263300	-0.181233	0.525581		
4	5	77	-0.110652	0.434760	0.494214		

```
1         0.517857  0.105684
2         0.492188  0.661930
3         0.501157  0.145552
4         0.430233  0.312139
```

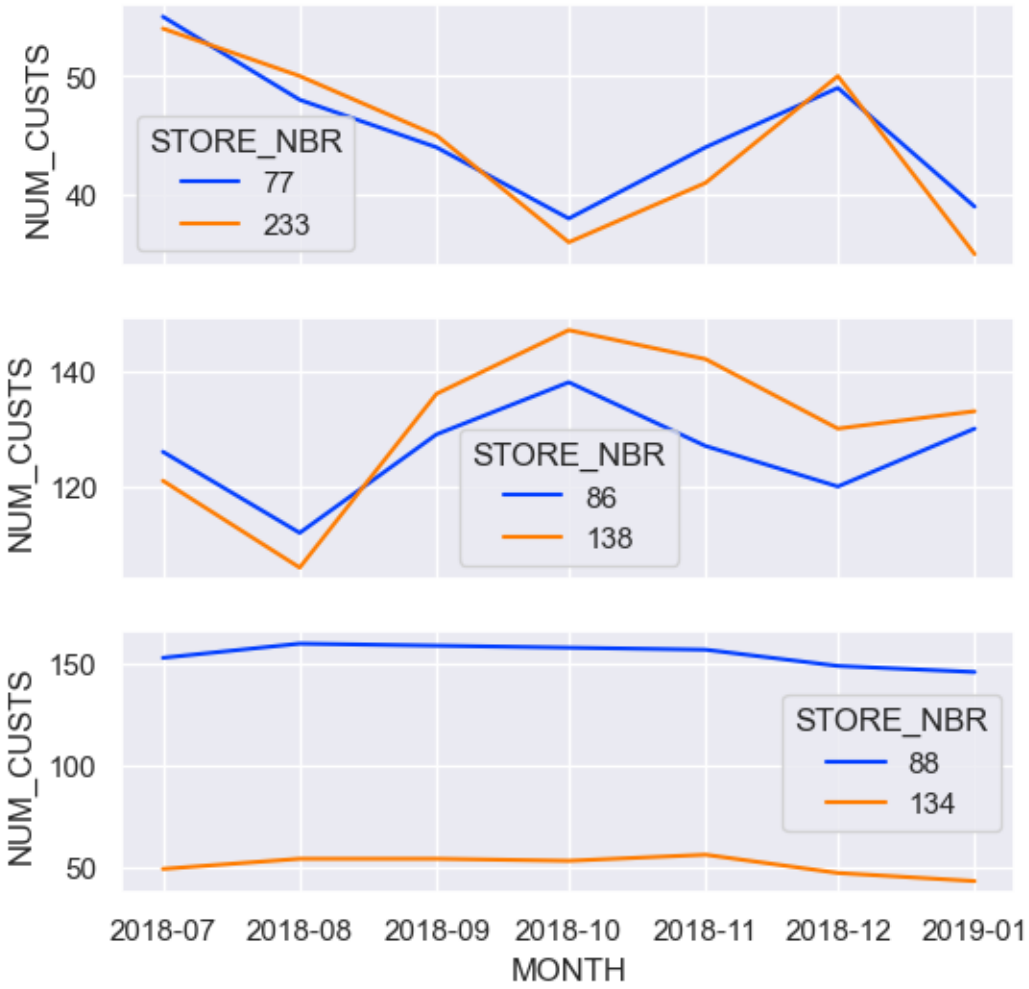
[ ]:
```
max_scores = comparison_df.groupby('Trial Store')['Score'].max().reset_index()
controls = max_scores.merge(comparison_df[['Control', 'Score']], how='inner',␣
 ↪on='Score')

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
```

[ ]:

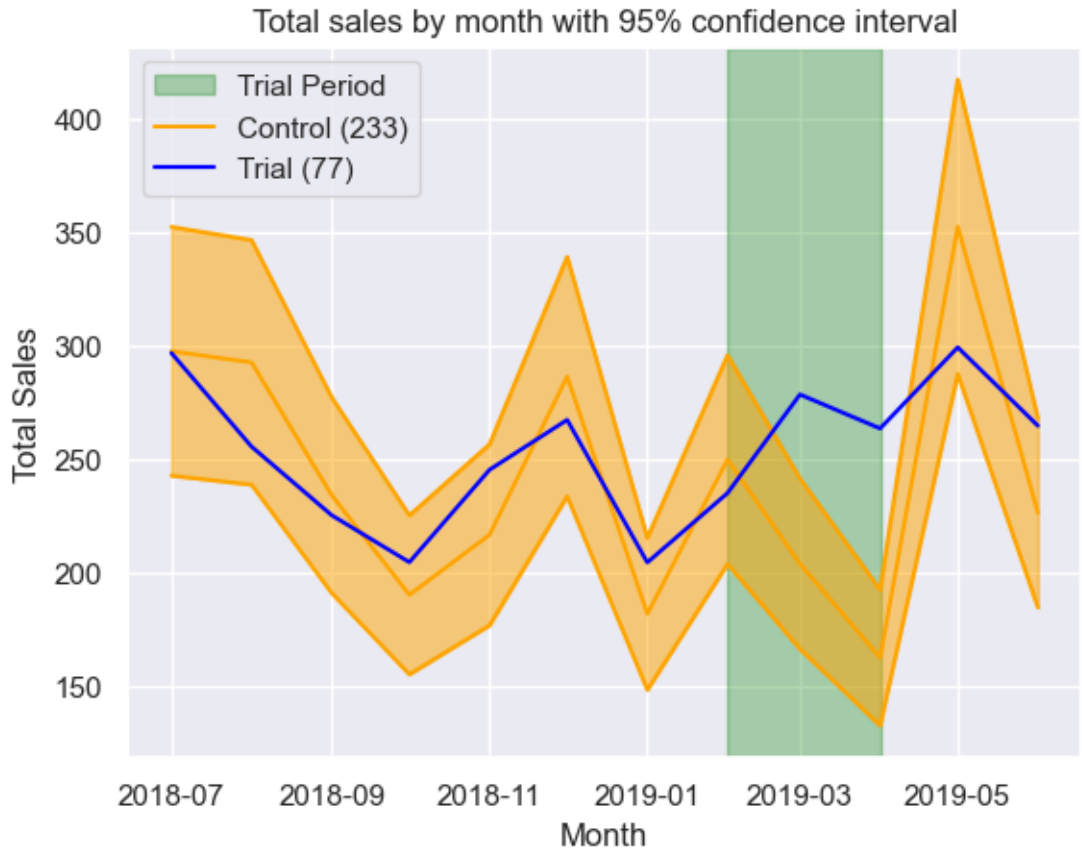
	MONTH	trial_sales	control_sales	scaled_control_sales	\
0	2018-07-01	296.8	290.7	297.565550	
1	2018-08-01	255.5	285.9	292.652187	
2	2018-09-01	225.2	228.6	233.998916	
3	2018-10-01	204.5	185.7	190.085733	
4	2018-11-01	245.3	211.6	216.597421	
5	2018-12-01	267.3	279.8	286.408121	
6	2019-01-01	204.4	177.5	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
```

[ ]:

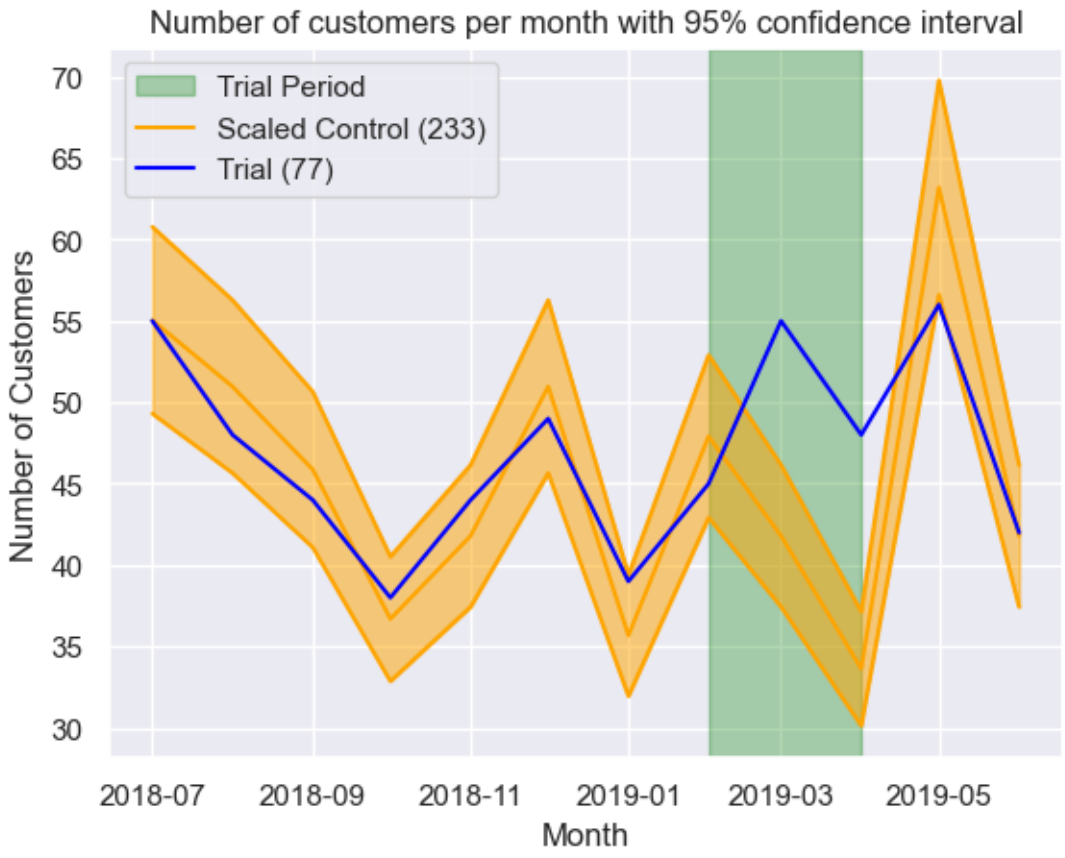
	MONTH	trial_num_custs	control_num_custs	scaled_control_num_custs	\
0	2018-07-01	55	54	55.041801	
1	2018-08-01	48	50	50.964630	
2	2018-09-01	44	45	45.868167	
3	2018-10-01	38	36	36.694534	
4	2018-11-01	44	41	41.790997	
5	2018-12-01	49	50	50.964630	
6	2019-01-01	39	35	35.675241	
7	2019-02-01	45	47	47.906752	
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
```

[ ]:
```
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
```

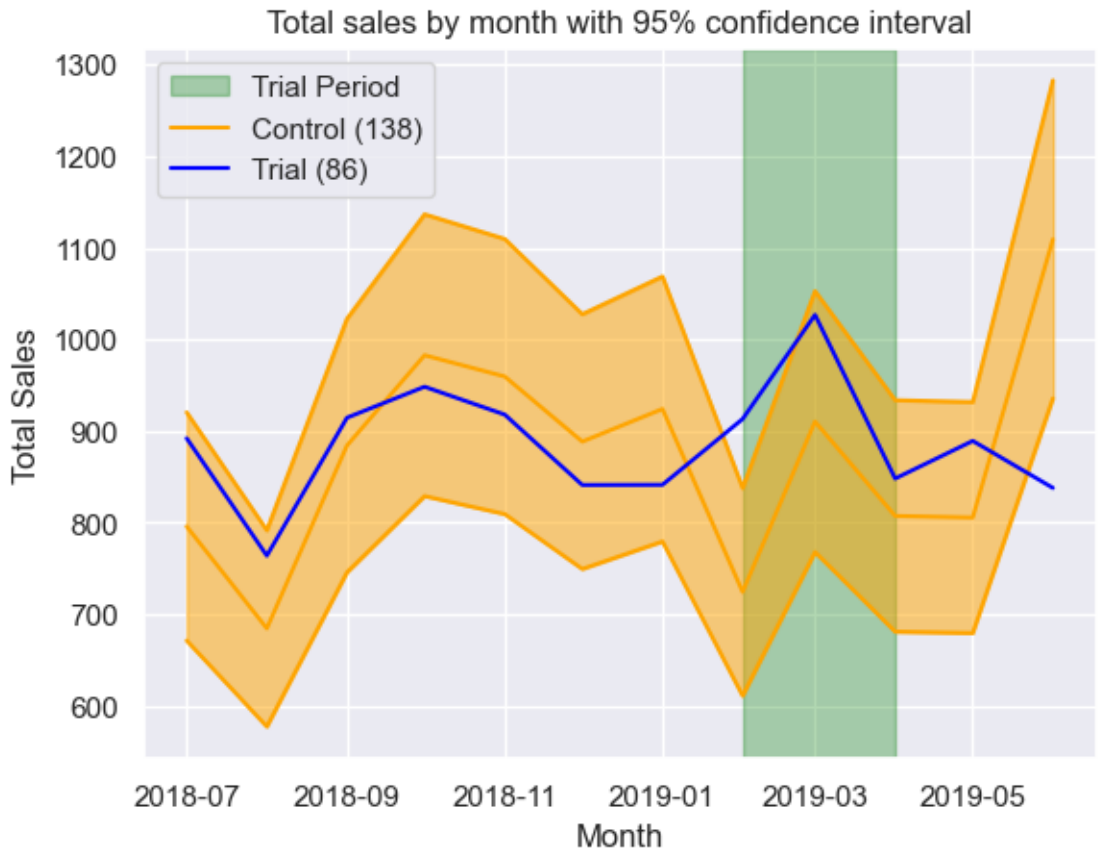
[ ]:

	MONTH	trial_sales	control_sales	scaled_control_sales	percentage_diff	t_value
0	2018-07-01	892.20	822.4	795.977327	12.088620	1.174582
1	2018-08-01	764.05	707.4	684.672132	11.593559	1.111285
2	2018-09-01	914.60	913.6	884.247186	3.432616	0.067850
3	2018-10-01	948.40	1015.4	982.776481	-3.497894	-0.818265
4	2018-11-01	918.00	991.4	959.547571	-4.329913	-0.924644
5	2018-12-01	841.20	918.0	888.505820	-5.324199	-1.051771
6	2019-01-01	841.40	954.8	924.123483	-8.951562	-1.515555
7	2019-02-01	913.20	748.6	724.548428	26.037124	2.957997
8	2019-03-01	1026.80	940.6	910.379711	12.788102	1.264016
9	2019-04-01	848.20	834.2	807.398208	5.053491	0.275091
10	2019-05-01	889.30	832.4	805.656040	10.382093	0.956390
11	2019-06-01	838.00	1146.0	1109.180468	-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
```

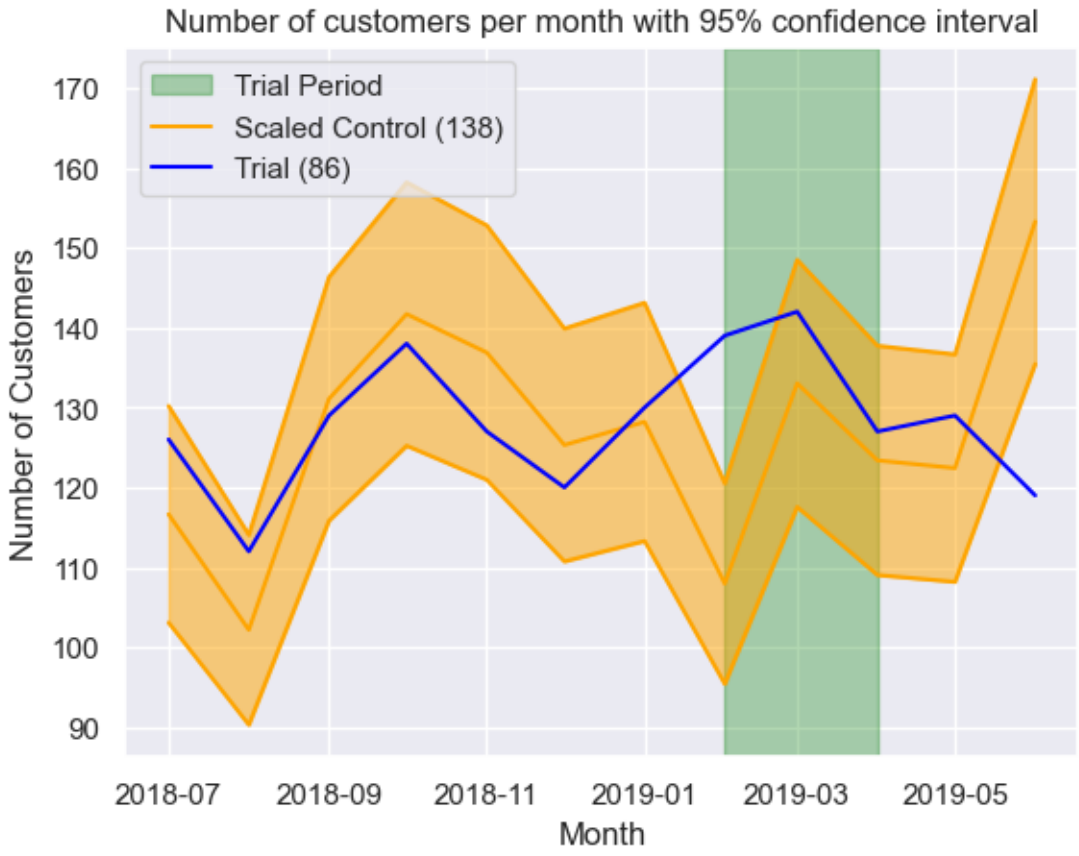
[ ]:

	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.

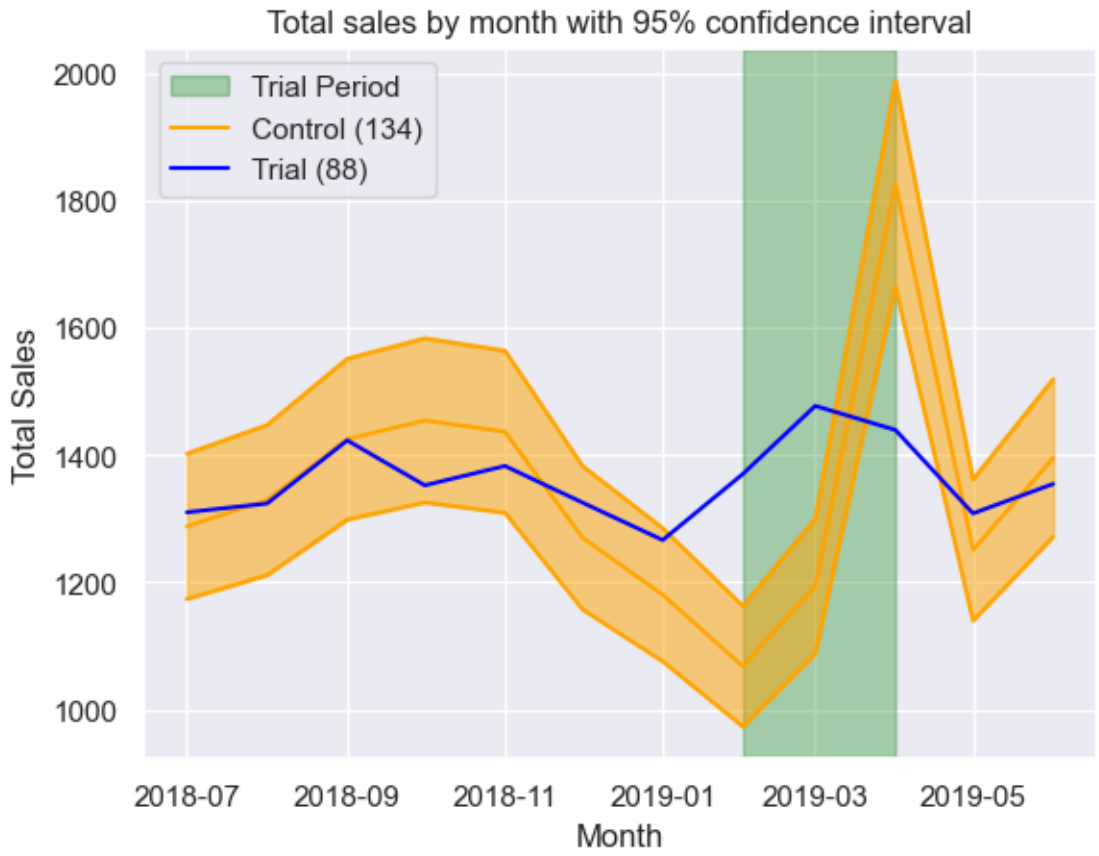
Let's consider the final trial store.

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

[ ]:

	MONTH	trial_sales	control_sales	scaled_control_sales	percentage_diff	t_value
0	2018-07-01	1310.00	419.20	1287.911965	1.715027	-0.262155
1	2018-08-01	1323.80	432.65	1329.234522	-0.408846	-0.741000
2	2018-09-01	1423.00	463.80	1424.936950	-0.135932	-0.679469
3	2018-10-01	1352.40	473.40	1454.431117	-7.015191	-2.230455
4	2018-11-01	1382.80	467.60	1436.611725	-3.745739	-1.493330
5	2018-12-01	1325.20	413.40	1270.092573	4.338851	0.329408
6	2019-01-01	1266.40	384.20	1180.381148	7.287379	0.994178
7	2019-02-01	1370.20	347.60	1067.934635	28.303733	5.732490
8	2019-03-01	1477.20	388.60	1193.899308	23.729027	4.701084
9	2019-04-01	1439.40	594.60	1826.794977	-21.206265	-5.429951
10	2019-05-01	1308.25	407.10	1250.737025	4.598327	0.387909
11	2019-06-01	1354.60	454.20	1395.442783	-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).

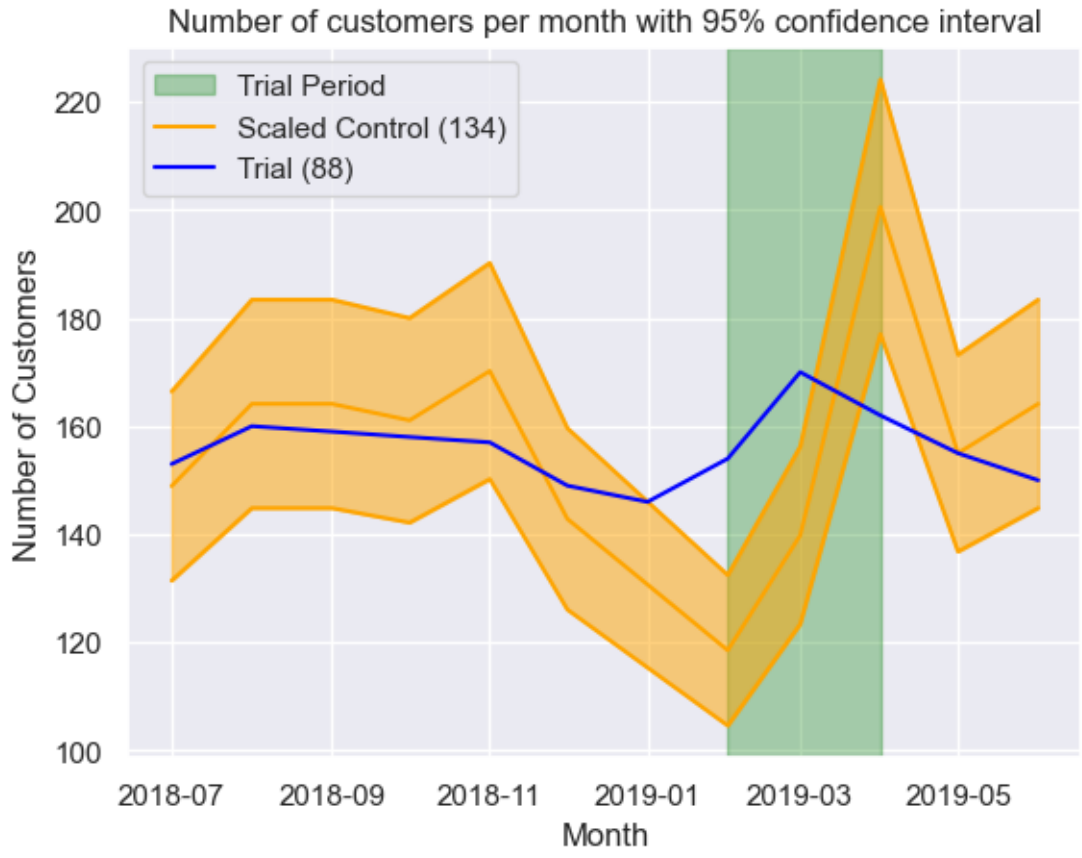
[ ]:
```
trial_num_custs3 = compare_num_custs(88, 134)
trial_num_custs3
```

[ ]:

	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.