Experimentation and uplift testing (Task 2)

Analyst: Albert Dellor

Email: dell.datascience@gmail.com

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Introduction

I have been approached by my client, the Category Manager for Chips, has asked me to test the impact of the new trial layouts with a data-driven recommendation to whether the trial layout should be rolled out to all their stores. This analysis seeks tp do just that.

Data description

This dataset was made available by Quantium as part of their Data Analytics Virtual Experience program. The dataset has 264834 by 12 rows and columns respectively.

- LYLTY_CARD_NBR: Loyalty card number of customers
- LIFESTAGE: life stage of customers
- PREMIUM_CUSTOMER: purchasing status of customers
- DATE: Data of transaction
- STORE_NBR: Store within which transaction took place
- LYLTY_CARD_NBR: Loyaity card number of customer
- TXN_ID: Transaction Identification
- PROD_NBR: Product number
- PROD_NAME: Product name
- PROD_QTY: Quantity of product purchased

Load the required libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
import matplotlib.dates as dates
%matplotlib inline
from sklearn.preprocessing import minmax_scale
from scipy.stats import t
```

Load the data from previous task

Examine data types of data

```
df = pd.read_csv('/data/notebook_files/QVI_data.csv',parse_dates=['DATE'])
print(df.shape)
df.info()
```

```
(264834, 12)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264834 entries, 0 to 264833
Data columns (total 12 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   LYLTY_CARD_NBR    264834 non-null  int64
 1   DATE              264834 non-null  datetime64[ns]
 2   STORE_NBR         264834 non-null  int64
 3   TXN_ID            264834 non-null  int64
 4   PROD_NBR          264834 non-null  int64
 5   PROD_NAME         264834 non-null  object
 6   PROD_QTY          264834 non-null  int64
 7   TOT_SALES         264834 non-null  float64
 8   PACK_SIZE         264834 non-null  int64
 9   BRAND             264834 non-null  object
 10  LIFESTAGE         264834 non-null  object
 11  PREMIUM_CUSTOMER  264834 non-null  object
dtypes: datetime64[ns](1), float64(1), int64(6), object(4)
memory usage: 24.2+ MB
```

```
df.sample(3)
```

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_S

Select control Stores

The client has selected store numbers 77, 86 and 88 as trial stores and want 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

First, we create the metrics of interest and filter to stores that are present throughout the pre-trial period. We define the measure calculations to use during the analysis

```
# Add a new month ID column in the data with the format yyyymm.
df['YEARMONTH'] = df.DATE.dt.strftime('20'+'%y-%m')

# Define the measure calculations to use during the analysis
totSales        = pd.DataFrame(df.groupby(['STORE_NBR','YEARMONTH'])['TOT_SALES'

nCustomers      = pd.DataFrame(df.groupby(['STORE_NBR','YEARMONTH'])['LYLTY_CARD

nTxnPerCust     = pd.DataFrame(df.groupby(['STORE_NBR','YEARMONTH'])['TXN_ID'].c
                  df.groupby(['STORE_NBR','YEARMONTH'])['LYLTY_CARD_NBR'].nuniqu

nChipsPerTxn    = pd.DataFrame(df.groupby(['STORE_NBR','YEARMONTH'])['PROD_QTY']
                  df.groupby(['STORE_NBR','YEARMONTH'])['TXN_ID'].count())

df['UNIT_COST'] = df['TOT_SALES']/df['PROD_QTY']

avgPricePerUnit = pd.DataFrame(df.groupby(['STORE_NBR','YEARMONTH'])['UNIT_COST'

index    = ['STORE_NBR','YEARMONTH']
metricss = totSales.merge(nCustomers,on=index)\
                         .merge(nTxnPerCust,on=index)\
                         .merge(nChipsPerTxn,on=index)\
                         .merge(avgPricePerUnit,on=index)

metricss.rename(columns={'TOT_SALES':'totSales',\
                          'LYLTY_CARD_NBR':'nCustomers',\
                          '0_x':'nTxnPerCust',\
                          '0_y':'nChipsPerTxn',\
                          'UNIT_COST':'avgPricePerUnit'},inplace=True)

measureOverTime = metricss.reset_index()

# Identify stores with full observation period i.e 12 months
stores = measureOverTime.groupby('STORE_NBR')['YEARMONTH'].count()

WithFullObs_index = stores[stores.values == 12].index.values

# Filter for stores with full Observation period
storeWithFullObs = measureOverTime.query('STORE_NBR in @WithFullObs_index')

preTrialMeasures = storeWithFullObs.query('YEARMONTH < "2019-02"')
TrialMeasures    = storeWithFullObs.query('YEARMONTH >= "2019-02"')
```

Now, we work out a way of ranking how similar each potential control store is to the trial store. We calculate how correlated the performance of each store is to the trial store.We create a function to calculate correlation for a measure, looping through each control store

```python
def calculate_correlation(input_table, metric_col, store_comparism):
    """
    calculate_correlation -  correlate performance of each  store to the trial s
    @input_table: metric table with potential comparison stores
    @metricCol: store metric used to calculate correlation on
    @storeComparison: store number of the trial store

    Returns: table of correlated performance of each store to the trial store
    """

    df_list = []
    store_numbers = input_table['STORE_NBR'].unique()
    j = store_comparism
    for i in store_numbers:
            if i != j:
                store1 = input_table.loc[input_table['STORE_NBR'] == i, metric_c
                store2 = input_table.loc[input_table['STORE_NBR'] == j, metric_c
                #calculate correlation between trial and control
                corr_measure = (np.corrcoef(store1,store2)[0,1])
                df_list.append({'Store1': i,
                                'Store2': j,
                                'Corr_measure': corr_measure
                               })

    calc_corr_table = pd.DataFrame(df_list, columns=['Store1','Store2','Corr_mea
    # display(calc_corr_table)
    return calc_corr_table
```

Apart from correlation, we also calculate a standardised metric based on the absolute difference between the trial store's performance and each control store's performance. We create a function to calculate a standardised magnitude distance for a measure looping through each control store

```
magnitudeMeasure = 1 - (measure - minDist)/(maxDist - minDist)]
```

```
def calculate_magnitude_distance(input_table, metric_col, store_comparison):
    """
    calculateMagnitudeDistance - standardised absolute difference between the
    trial store's performance and each control store
    @input_table: metric table with potential comparison stores
    @metricCol: store metric used to calculate correlation on
    @storeComparison: store number of the trial store

    Returns: table of standardised magnitude distance of each store to the
    trial store
    """
    calc_dist_table = pd.DataFrame(columns=['Store1', 'Store2', 'YEARMONTH', 'me
    store_numbers = input_table['STORE_NBR'].unique()
    for i in store_numbers:
        if i != store_comparison:
            calculated_measure = pd.DataFrame({
                'Store2': [store_comparison] * len(input_table[input_table['STOR
                'Store1': [i] * len(input_table[input_table['STORE_NBR'] == i]),
                'YEARMONTH': input_table[input_table['STORE_NBR'] == i]['YEARMON
                'measure': abs(input_table[input_table['STORE_NBR'] == store_com
                                input_table[input_table['STORE_NBR'] == i][metri
            })

            calc_dist_table = pd.concat([calc_dist_table, calculated_measure], i

    # Standardise the magnitude distance so that the measure ranges from 0 to 1
    min_max_dist = calc_dist_table.groupby(['Store2', 'YEARMONTH'])['measure'].a
    min_max_dist.columns = ['Store2', 'YEARMONTH', 'minDist', 'maxDist']
    dist_table = pd.merge(calc_dist_table, min_max_dist, on=['Store2', 'YEARMONT
    dist_table['mag_measure'] = 1 - ((dist_table['measure'] - dist_table['minDis
                                      (dist_table['maxDist'] - dist_table['
    final_dist_table = dist_table.groupby(['Store1', 'Store2'])['mag_measure'].m
    return final_dist_table
```

We use the functions to find the control stores. We select control stores based on how similar monthly total sales in dollar amounts and monthly number of customers are to the trial stores. We combine all the scores calculated using our function to create a composite score to rank on using a simple average of the correlation and magnitude scores for each driver

```python
def combined_score(metric_col,trial_store):
    """
    combined_score - creates combined score composed of correlation and magnitud
    @metric_col: store metric used to calculate correlation/magnitude on
    @trial_store: trial store number

    Returns: Dataframe of combined scores of controls against trial store
    """

    # merge the correlations table with the magnitude table.
    composite_score =   calculate_correlation(preTrialMeasures,metric_col,trial_
                        .merge(calculate_magnitude_distance(preTrialMeasures,met
                        ,trial_store)[['Store1','mag_measure']]
                        ,left_on = 'Store1',right_on='Store1')

    # combine score composed of correlation and magnitude
    # calculate simple average on the scores
    composite_score['combined_score'] = 0.5 * composite_score['Corr_measure']\
                                        + 0.5 * composite_score['mag_measure']
    return composite_score
```

This function calculates the final control score combining metrics derived from the combined_score function. The store with the highest score is then selected as the control store since it is most similar to the trial store

```python
def findcontrol(trialstore, metric_col1, metric_col2):
    """
    combineScores - creates final control score combining metrics derived from t
    @trial_store: trial store number
    @metric_col1: first store metric used for score combination (totSales)
    @metric_col2: second store metric used for score combination (nCustomers)

    Returns: DataFrame of finalControlScore
    """

    # combined score of totSales composed of correlation and magnitude scores
    score_nsales = combined_score(metric_col1,trialstore)

    # combined score of nCustomers composed of correlation and magnitude scores
    score_ncustomers = combined_score(metric_col2,trialstore)

    # merge the two dataframes
    score_control = (score_nsales[['Store1','Store2','combined_score']])\
                    .merge(score_ncustomers[['Store1','combined_score']]
                    ,left_on='Store1',right_on='Store1')

    # calculate combine score i.e finalComtrolScore, via a simple average
    # and sorting in descending order
    score_control['finalControlScore'] = (score_control.combined_score_x * 0.5)
                                       + (score_control.combined_score_y * 0.5)

    score_control.sort_values(by='finalControlScore', ascending=False, inplace=T

    print('Based on {} and {} drivers, the most appropriate control store \nfor
          .format(metric_col1, metric_col2, trialstore, score_control.Store1[:1]
```

Function checks visually if the drivers are indeed similar in the period before the trial

```python
def plottrends(control, trial,data = measureOverTime):
    """
    plottrends - plots trial and control trends based on a driving metric
    metric_col: store metric used to plot
    @trial: trial store number
    @control: control store number
    """

    measureovertimesales = data.query("YEARMONTH < '2019-03'").copy()

    # Categorize stores into trial, control, and other stores
    measureovertimesales['Store_type'] =  np.where(measureovertimesales.STORE_NB
                                          np.where(measureovertimesales.STORE_NB
                                                   'other_stores'))

    # Calculate total sales by month and store type
    pastsales = measureovertimesales.groupby(['YEARMONTH','Store_type'])\
                .agg({'totSales':'mean'}).reset_index()

    pastcustomers = measureovertimesales.groupby(['YEARMONTH','Store_type'])\
                    .agg({'nCustomers':'mean'}).reset_index()

    #Plot totSales thrend
    plt.figure(figsize=(14,6))
    # plt.subplot(2,1,1)
    sb.lineplot(x = 'YEARMONTH', y='totSales', hue='Store_type',data=pastsales,l
    # get datetime in months
    date = pd.to_datetime(pastsales.YEARMONTH.unique())
    date = date.strftime('%b')
    plt.xticks(plt.xticks()[0],date)

    plt.title("totSales over time")
    plt.ylabel('totSales')
    plt.xlabel('Month of operation')
    # adjust plot up
    plt.subplots_adjust(bottom=0.1)
    # place legend at bottom of plot
    plt.legend(loc='upper center', bbox_to_anchor=(0.5, -0.15), ncol=3)

    #Plot nCustomers thrend
    plt.figure(figsize=(14,6))
    sb.lineplot(x = 'YEARMONTH', y='nCustomers', hue='Store_type',data=pastcusto
    plt.xticks(plt.xticks()[0],date)
    plt.title("nCustomers over time")
    plt.ylabel('totSales')
    plt.xlabel('Month of operation')
    # adjust plot up
    plt.subplots_adjust(bottom=0.1)
    # place legend at bottom of plot
    plt.legend(loc='upper center', bbox_to_anchor=(0.5, -0.15), ncol=3)

    plt.figure(figsize=(14,6))
    # plt.subplot(2,1,1)
    ax = sb.lineplot(x = 'YEARMONTH', y='totSales', hue='Store_type',data=pastsa
    # get datetime in months
    date = pd.to_datetime(pastsales.YEARMONTH.unique())
```

```python
    date = date.strftime('%b')
    plt.xticks(plt.xticks()[0],date)

    plt.gca().spines['left'].set_visible(False)
    plt.gca().spines['top'].set_visible(False)
    plt.gca().spines['right'].set_visible(False)

    # remove x and y tick marks
    plt.tick_params(axis='y', which='both', left=False)
    plt.tick_params(axis='x', which='both', bottom=False)

    plt.ylabel('Sales')
    plt.xlabel('')

    # adjust plot up
    plt.subplots_adjust(bottom=0.1)
    # place legend at bottom of plot
    plt.legend(loc='upper center', bbox_to_anchor=(0.5, -0.15), ncol=3)
    plt.savefig('trial vrs control sales.png', dpi=120, bbox_inches='tight', fac
```

calcpretrialpercentageDiff function calculates the absolute percentage different between scale pre-trial control sales and pre-trial trial store

```python
def scale(metric,control, trial):
    """
    scale - calculate scaling factor
    metric_col: store metric used to plot
    @trial: trial store number
    @control: control store number

    Return: scaling factor
    """

    control_store = preTrialMeasures.query("STORE_NBR == @control")[metric]
    trial_store   = preTrialMeasures.query("STORE_NBR == @trial")[metric]

    # Calculate ScalingFactor
    scalingFactorForControlmetric = np.sum(trial_store)/np.sum(control_store)

    return scalingFactorForControlmetric


def calcpretrialpercentageDiff(metric,control, trial):
    """
    CalcpretrialpercentageDiff - use scaling factor to calculate absolute percen
                                scale pre-trial control sales  and pre-trial tri
    metric_col: store metric used to plot
    @trial: trial store number
    @control: control store number

    Return: DataFrame with scaled pre-trial control sales  and pre-trial
            trial store sales and absolute percentage difference
    """

    control_store = measureOverTime.query("STORE_NBR == @control").copy()
    trial_store   = measureOverTime.query("STORE_NBR == @trial").copy()

    scalingFactor = scale(metric,control, trial)

    control_store[metric] = control_store[metric] * scalingFactor
    control_store.rename(columns={metric:'control'+metric},inplace=True)
    trial_store = trial_store.merge(control_store[['YEARMONTH','control'+metric]
    trial_store['percentageDiff'] = (np.abs(trial_store['control'+metric].values
                                        /trial_store['control'+metric].value

    return trial_store
```

Assessment of trial.

- The trial period goes from the start of February 2019 to April 2019.
- The **Analyse function**, checks to see if there has been an uplift in overall chip sales.

```
def plot(metric,data):
    """
    plot - plots metrics against 95th and 5th percentile of t-distribution
    @metric: metrics to plot
    @data: DataFrame to plot
    """

    # plots metrics against 95th and 5th percentile of t-distribution
    # plt.figure(figsize=(14,6))
    sb.lineplot(x='YEARMONTH', y= 't-value', data=data, linewidth=5)
    plt.scatter('YEARMONTH', y='t-value',data=data)
    sb.lineplot(x='YEARMONTH', y= '95th-percentile', label = '95th-percentile',
    plt.title('t-Distribution')
    plt.xlabel('Month of operation')
    plt.ylabel('t-distribution')


def Analyse(metric,control, trial):
    """
    Analyse - analyse trial period trial and control data
    @metric_col: store metric used to plot
    @trial: trial store number
    @control: control store number

    Return: Conclusion whether trial store is sigif ically different from contro
    """

    percentageDiff = calcpretrialpercentageDiff(metric,control, trial)

    # calculate standard deviation for %difference from pretrial data
    stdDev  = np.std(percentageDiff[percentageDiff['YEARMONTH'] < '2019-02']['pe

    percentageDiff = percentageDiff.query("YEARMONTH >= '2019-02' & YEARMONTH <=

    percentageDiff['t-value'] = (percentageDiff['percentageDiff'].values - 0)/st

    # #calculate 95th pecentile of t-distribution
    percentageDiff['95th-percentile'] = t.ppf(0.95, 7)

    display(percentageDiff[['STORE_NBR','YEARMONTH','percentageDiff','t-value','

    # print('Null hypothesis: there is no significant difference between trial a
    # print('\nAlternate hypothesis: there is significant difference between tri
    # print('\nWe can reject the null hypothesis if the t-value is greater than

    if sum(np.round(percentageDiff['t-value'],0) > np.round(percentageDiff['95th
        print("\nConclusion: There is a statistically significant difference bet
    else:
        print("\nConclusion: There is no statistically significant difference be

    plot(metric,percentageDiff)

    # copy the dataframe measureOverTime to measureOverTimeSales
    measureOverTimeSales = measureOverTime.copy()

    # create a new column 'Store_type' based on the store numbers
```

```
measureOverTimeSales['Store_type'] = np.where(measureOverTimeSales['STORE_NB
                                    np.where(measureOverTimeSales['STORE_NBR

# group by 'YEARMONTH' and 'Store_type' and calculate the mean of 'totSales'
pastSales = measureOverTimeSales.groupby(['YEARMONTH', 'Store_type'])[metric

# filter for 'Trial' and 'Control' stores only
pastSales = pastSales[pastSales['Store_type'].isin(['Trial', 'Control'])]

# filter for 'Control' store only and create a 95th percentile confidence in
pastSales_Controls95 = pastSales[pastSales['Store_type'] == 'Control'].copy(
pastSales_Controls95[metric] = pastSales_Controls95[metric] * (1 + stdDev *
pastSales_Controls95['Store_type'] = 'Control 95th% CI'

# filter for 'Control' store only and create a 5th percentile confidence int
pastSales_Controls5 = pastSales[pastSales['Store_type'] == 'Control'].copy()
pastSales_Controls5[metric] = pastSales_Controls5[metric] * (1 - stdDev * 2)
pastSales_Controls5['Store_type'] = 'Control 5th% CI'

# combine all dataframes
trialAssessment = pd.concat([pastSales, pastSales_Controls95, pastSales_Cont

# plot the data
plt.figure(figsize=(14, 6))
sb.lineplot(x='YEARMONTH', y=metric, data = trialAssessment.where(trialAsses
sb.lineplot(x='YEARMONTH', y=metric, data = trialAssessment.where(trialAsses
sb.lineplot(x='YEARMONTH', y=metric, data = trialAssessment.where(trialAsses
sb.lineplot(x='YEARMONTH', y=metric, data = trialAssessment.where(trialAsses
# date = pd.to_datetime(trialAssessment.YEARMONTH)
# date = date.strftime('%b')
# plot transparent fill
plt.fill_between(trialAssessment['YEARMONTH'], pastSales_Controls95[metric].

# Remove left, top and right border lines
plt.gca().spines['left'].set_visible(False)
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)

# rename x-axis to months
date = pd.to_datetime(trialAssessment.YEARMONTH.unique())
date = date.strftime('%b')
plt.xticks(plt.xticks()[0],date)

# remove x and y tick marks
plt.tick_params(axis='y', which='both', left=False)
plt.tick_params(axis='x', which='both', bottom=False)
# plt.xlabel(plt.xlabel()[0],date)
plt.title('Total '+metric+' by month')
plt.xlabel('Month of operation')
plt.ylabel('Total '+metric)
# plt.ylabel('Number of customer')
# plt.xlabel('')
# plt.xticks(rotation=35)
# plt.legend()

# adjust plot up
plt.subplots_adjust(bottom=0.1)
# place legend at bottom of plot
```

```
    plt.legend(loc='upper center', bbox_to_anchor=(0.5, -0.15), ncol=3)
    # plt.savefig('trial number of customers uptick.png', dpi=120, bbox_inches='

    plt.show()
```

Trial store 77

Find control store for trial store 77

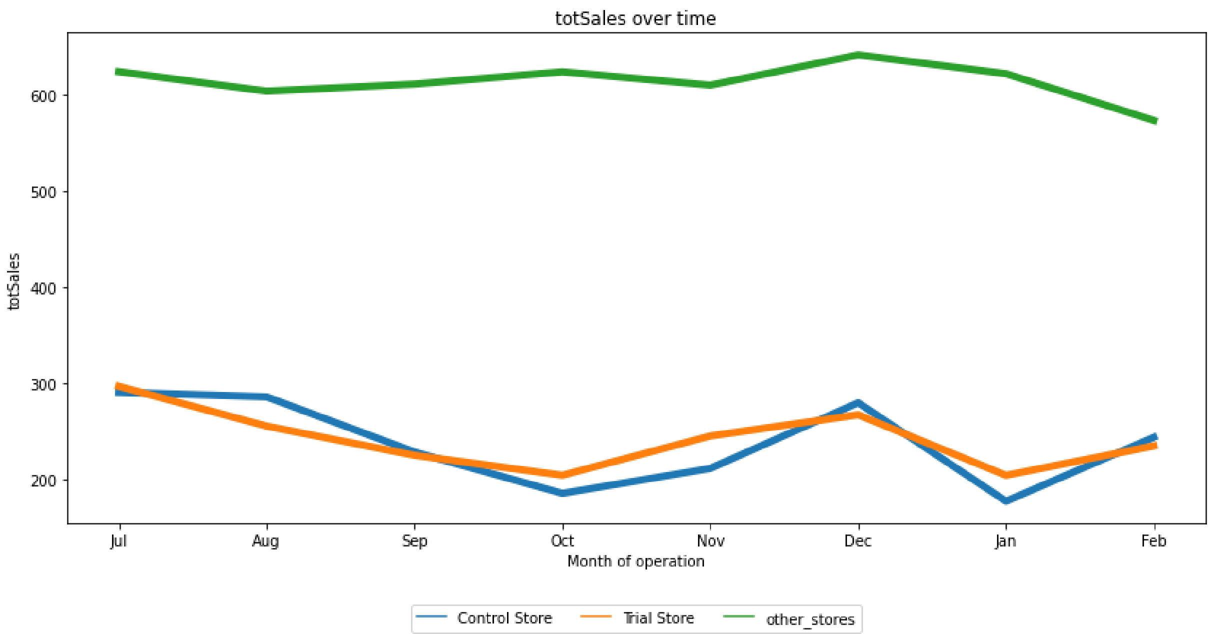
```
findcontrol(77,'totSales','nCustomers')
```

```
Based on totSales and nCustomers drivers, the most appropriate control store
for trial store 77 is 233.
```

Check visually if the totSales and nCustomers of control store are indeed similar to trial store 77 in before the trial.

```
plottrends(233,77)
```

Download



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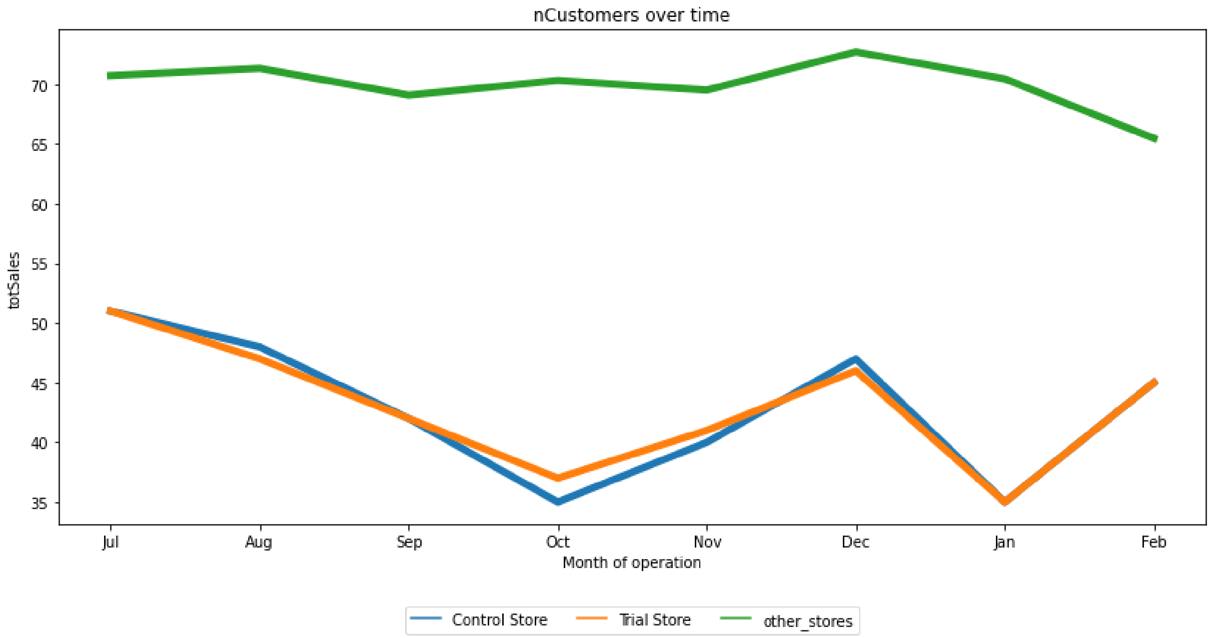

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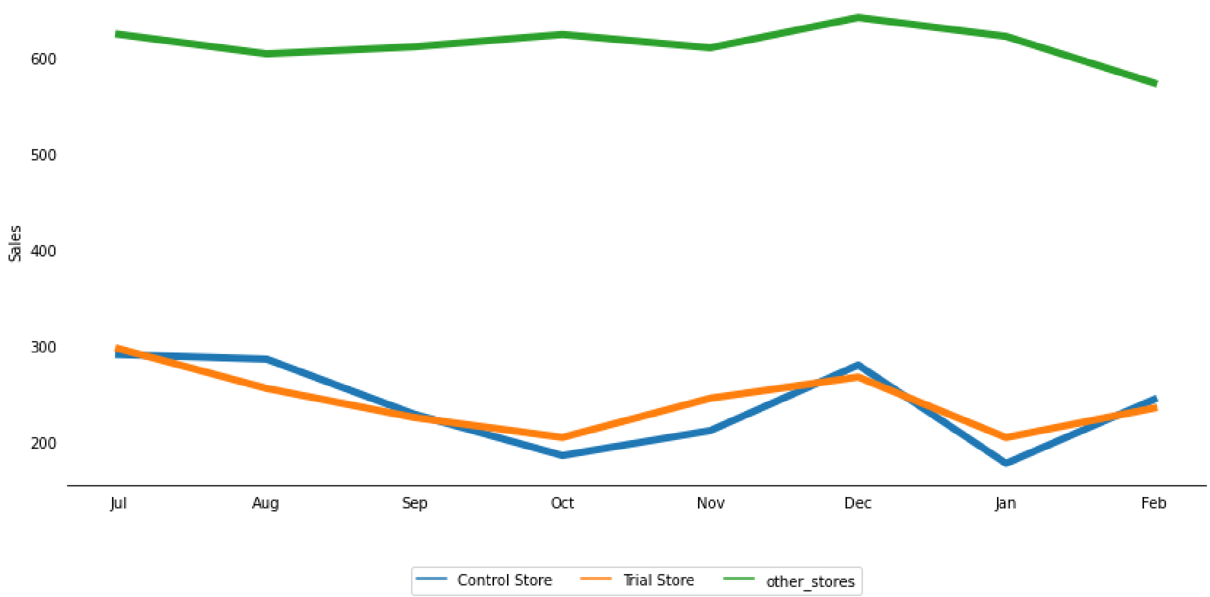


It is evident that the trial and control store have similar trends in terms of both total sales and number of customers, compared to the other stores. This comfirms that prior to the trial, they are similar.

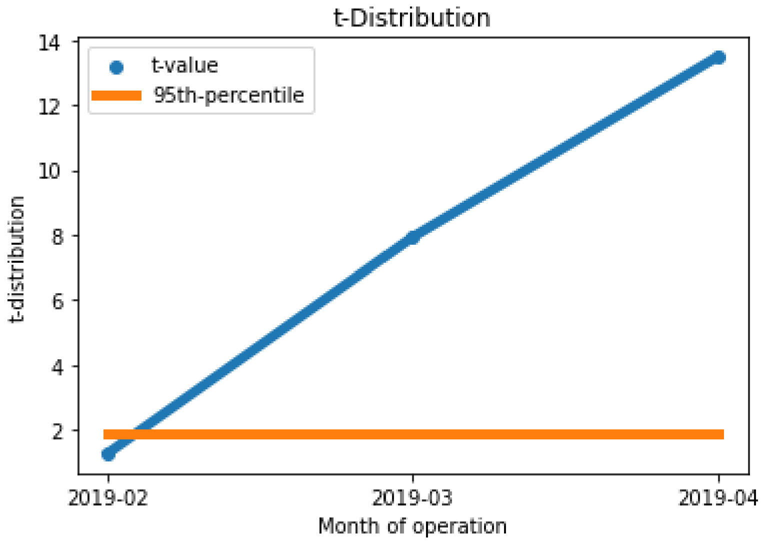
Assesse differences in total sales between trial store and control

```
Analyse('totSales',233, 77)
```

```
Conclusion: There is a statistically significant difference between trial and
```

	STORE_NBR	YEARMONTH	percentageDiff	t-value	95th-percentile

Download



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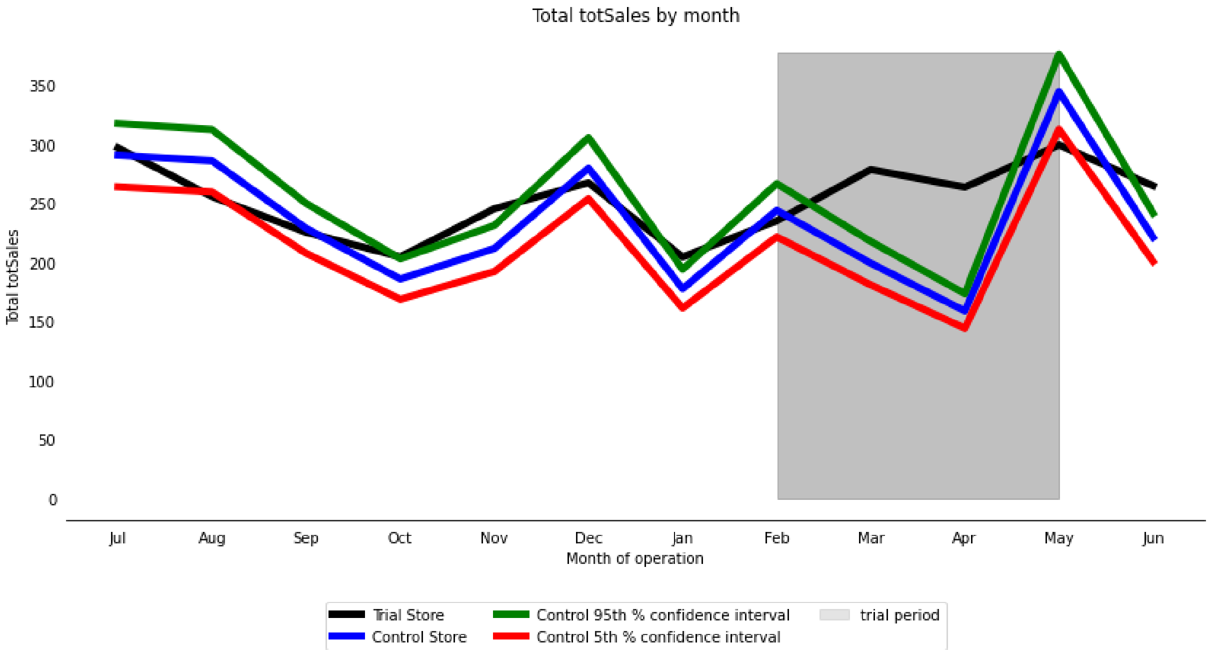


We notice that the t-value for March and April is considerably higher than the 95th percentile value of the t-distribution. This implies that the growth in sales of the trial store in these two months is statistically more significant than the control store.

The findings suggest that there is a significant difference in the total sales of trial store 77 compared to its control store sales during the trial period, as the performance of the trial store falls beyond the 5% to 95% confidence interval of the control store for two out of the three trial months.

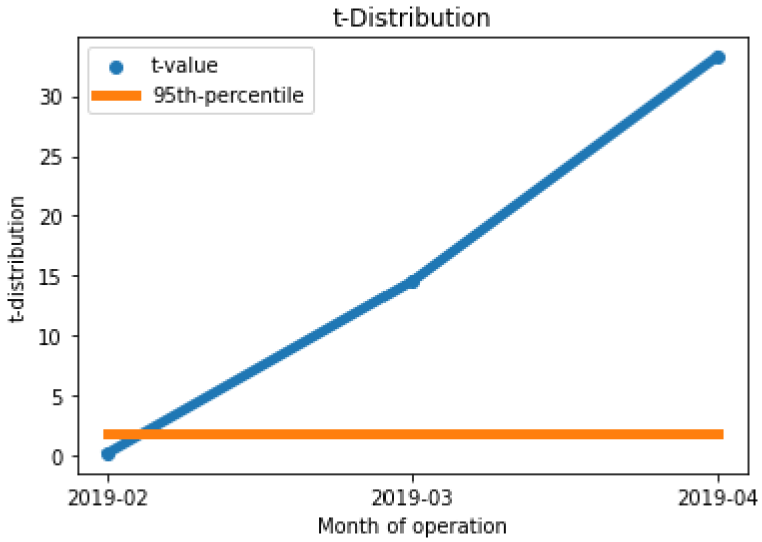
Assesment for number of customers

```
Analyse('nCustomers',233, 77)
```

```
Conclusion: There is a statistically significant difference between trial and
```

	STORE_NBR	YEARMONTH	percentageDiff	t-value	95th-percentile

Download



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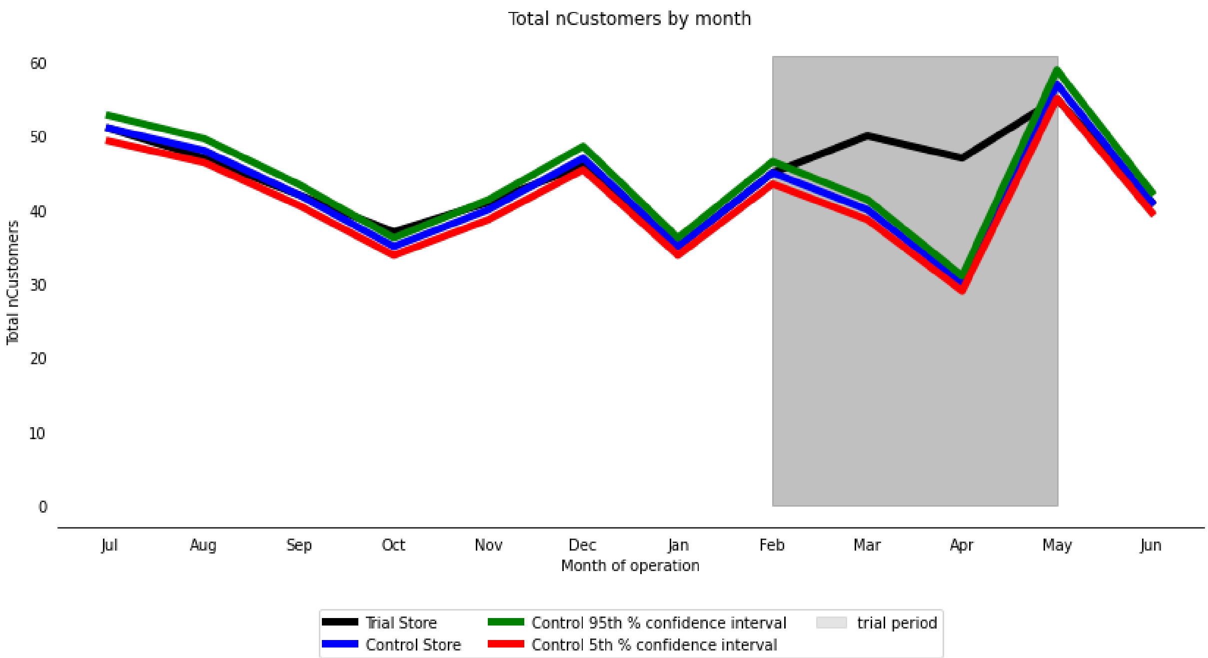


The number of customers in trial store 77 during the trial period is significantly different from its control store as the trial store's performance is outside the 5% to 95% percentile of the t-distribution in two of the three trial months, just like the total sales. Therefore, it can be concluded that both the total sales and the number of customers in the trial and control stores are significantly different.

Trial store 86

Find control store for trial store 86

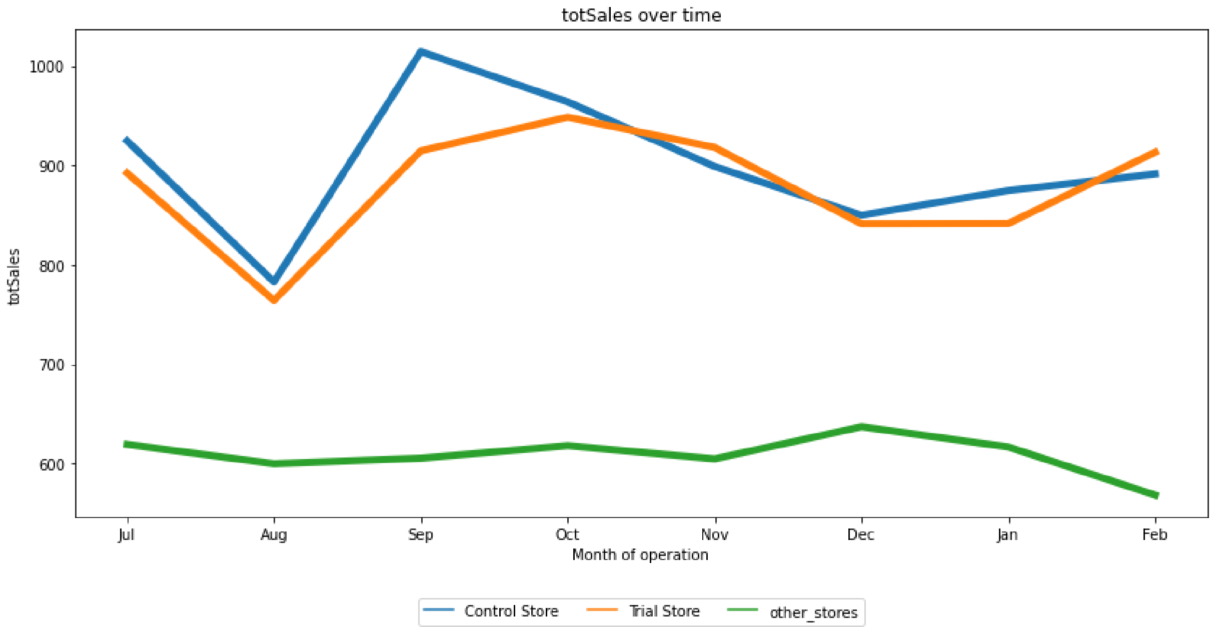
```
findcontrol(86,'totSales','nCustomers')
```

```
Based on totSales and nCustomers drivers, the most appropriate control store
for trial store 86 is 155.
```

Check visually if the drivers are indeed similar in the period before the trial

```
plottrends(155,86)
```

Download



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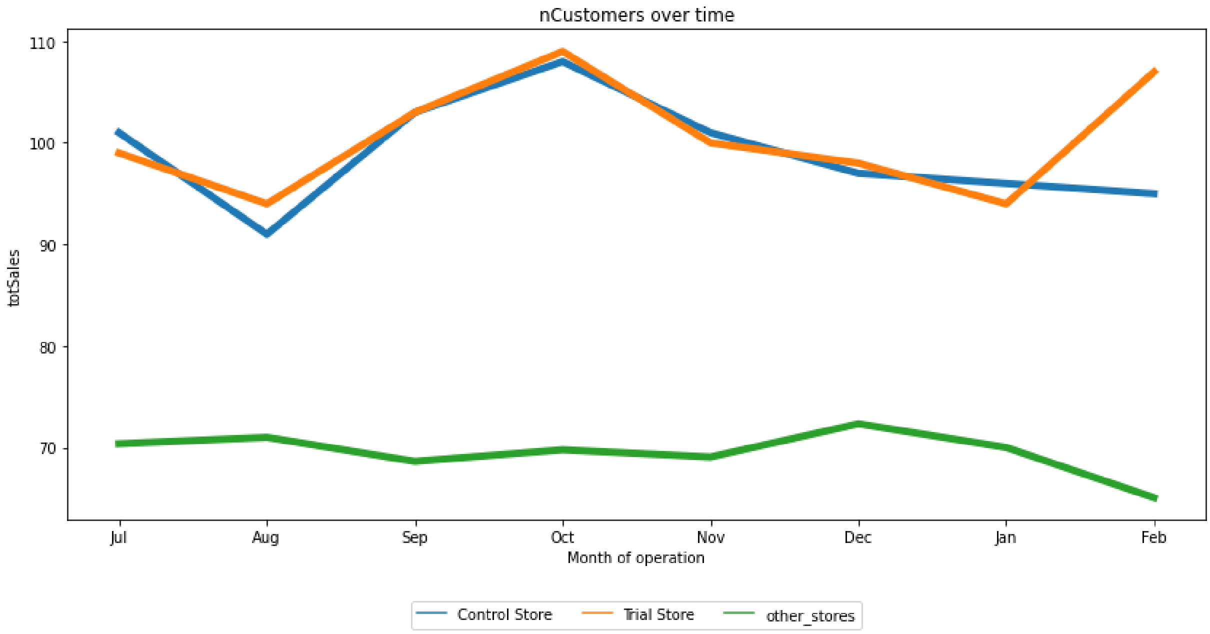

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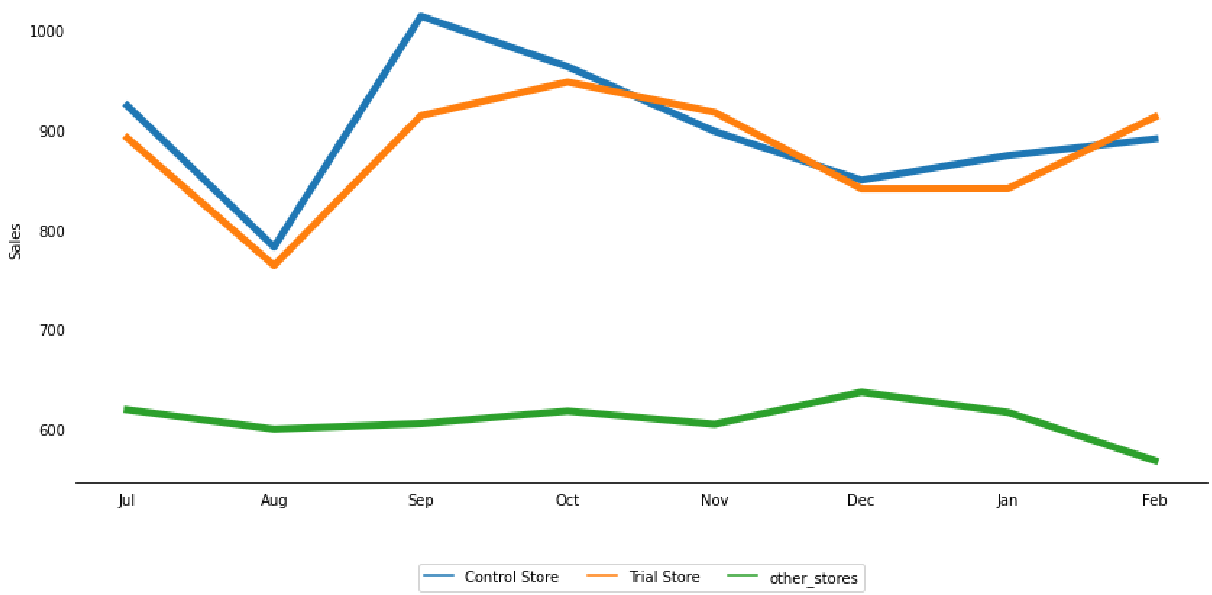


Again, it is evident that the trial and control stores have similar trends and are higher both in the total sales and number of customers, compared to the other stores.

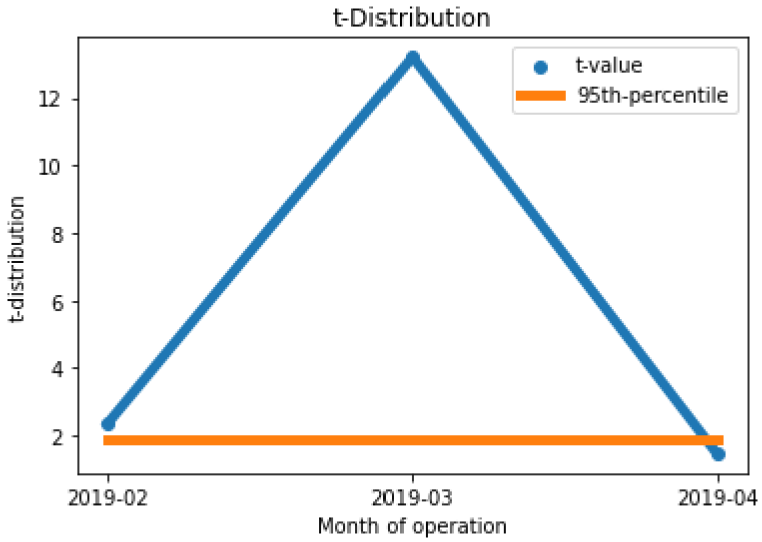
Assessment for totSales

```
Analyse('totSales',155, 86)
```

```
Conclusion: There is no statistically significant difference between trial and
```

	STORE_NBR	YEARMONTH	percentageDiff	t-value	95th-percentile

Download



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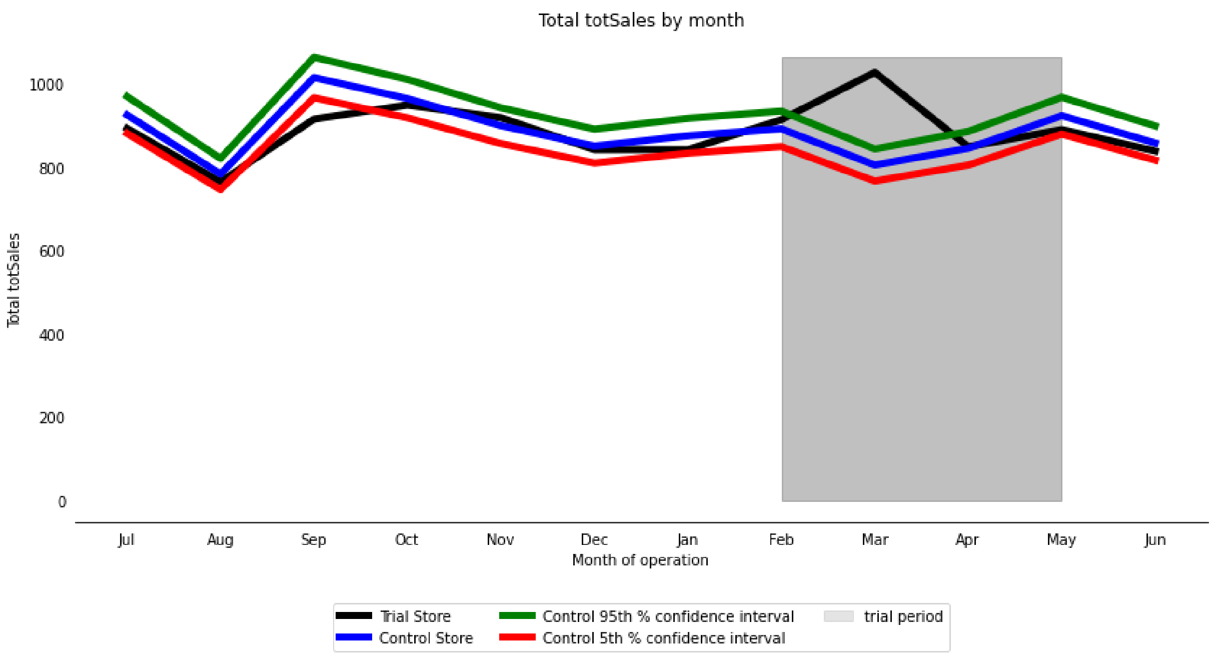


Based on the results, it can be concluded that there is no significant difference between the trial store 86 and its control store during the trial period. This is because the performance of the trial store falls within the 5% to 95% confidence interval of the control store for two out of the three trial months.

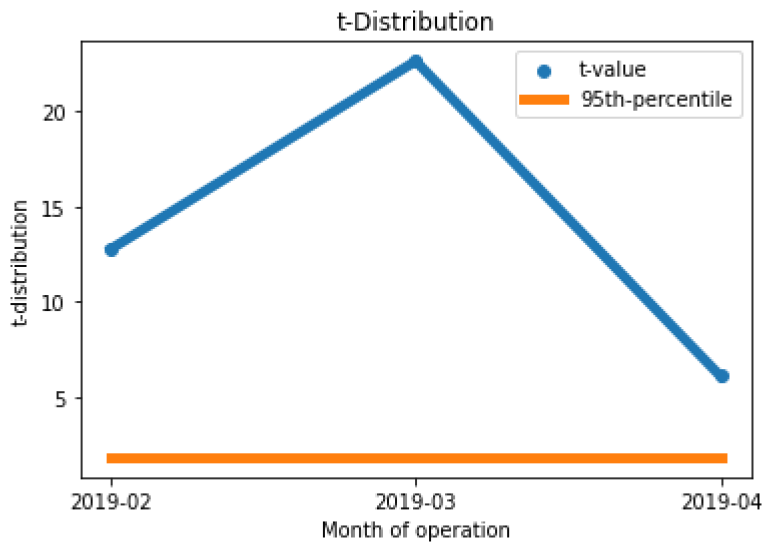
Assessment for nCustomers

```
Analyse('nCustomers',155, 86)
```

```
Conclusion: There is a statistically significant difference between trial and
```

	STORE_NBR	YEARMONTH	percentageDiff	t-value	95th-percentile

Download



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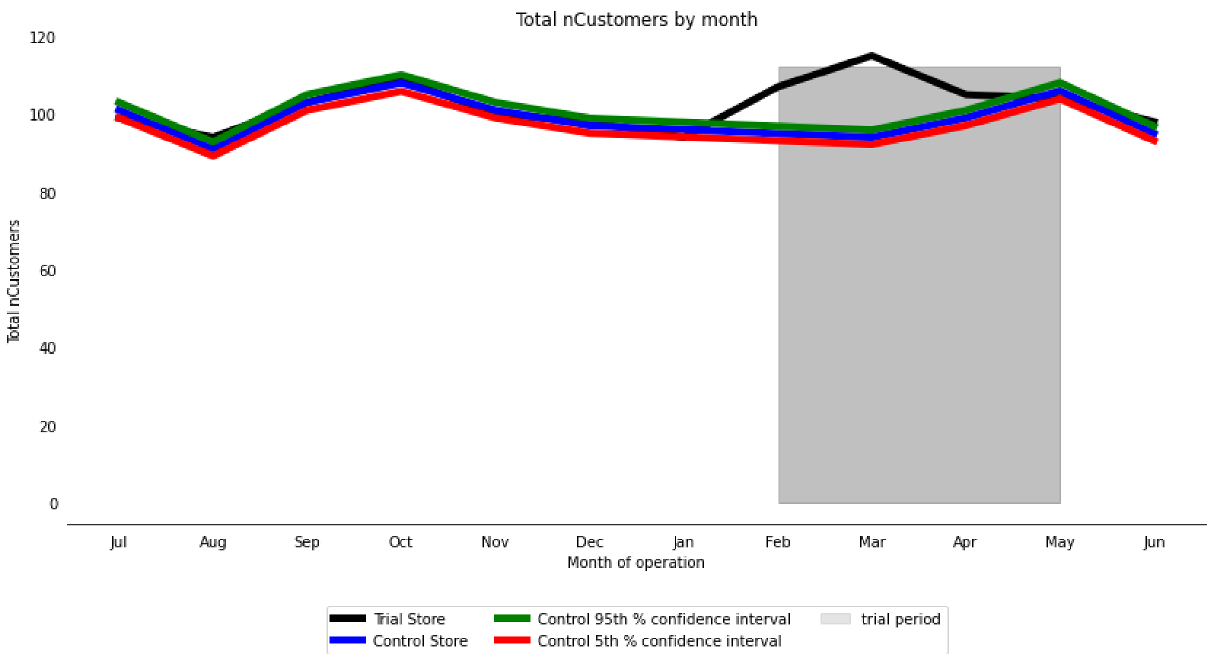


It appears that there was a notable increase in the number of customers in all the three months, indicating that the trial had a substantial impact on the customer count at store 86. However, as previously mentioned, there was no significant increase in sales. To obtain a clear understanding, it would be appropriate to consult with the Category Manager to determine whether there were any exclusive deals or promotions in the trial store that might have drawn in more customers at the cost of lower sales.

Trial store 88

Find control store for trial store 88

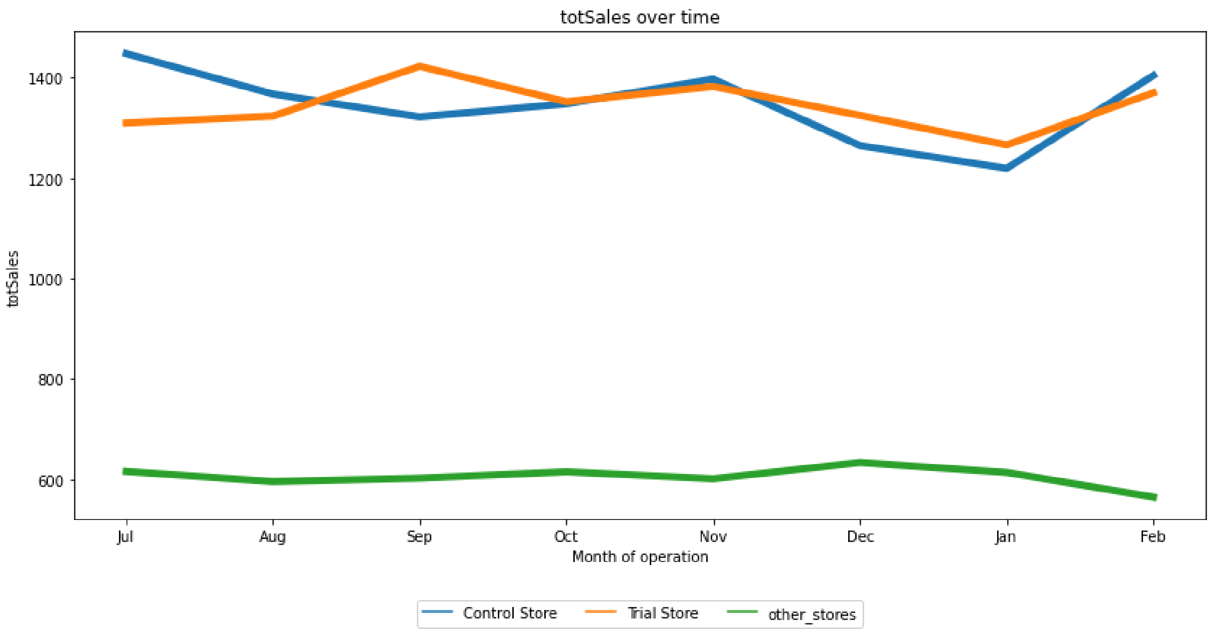
```
findcontrol(88, 'totSales','nCustomers')
```

```
Based on totSales and nCustomers drivers, the most appropriate control store
for trial store 88 is 237.
```

Check visually if the drivers are indeed similar in the period before the trial

```
plottrends(237,88)
```

Download



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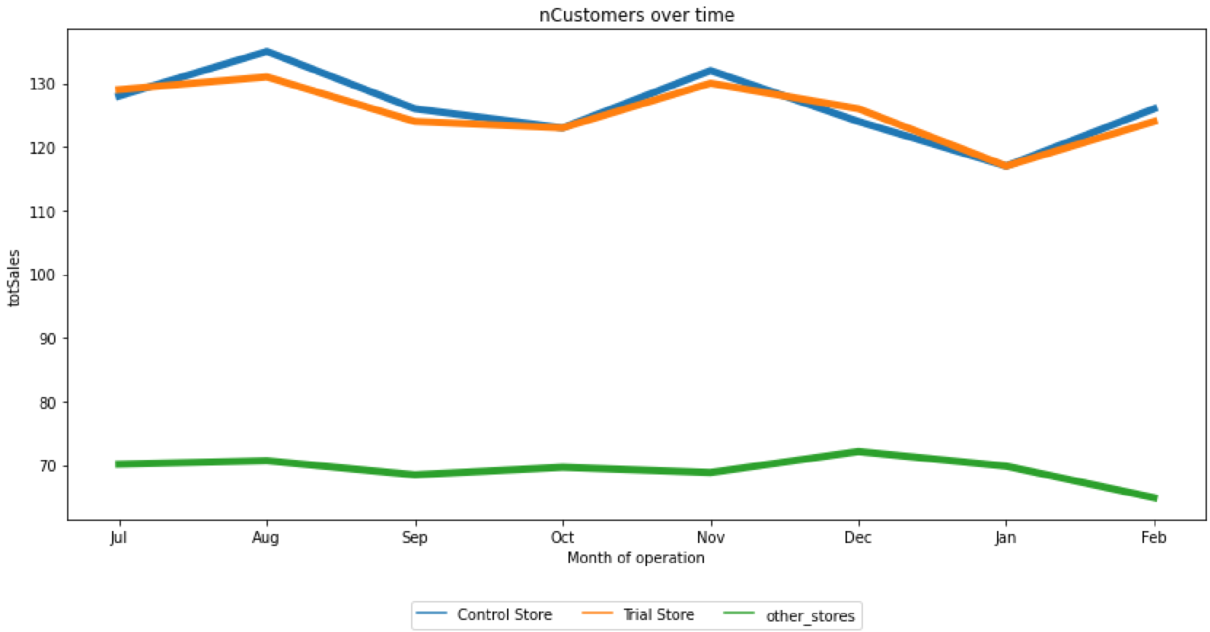

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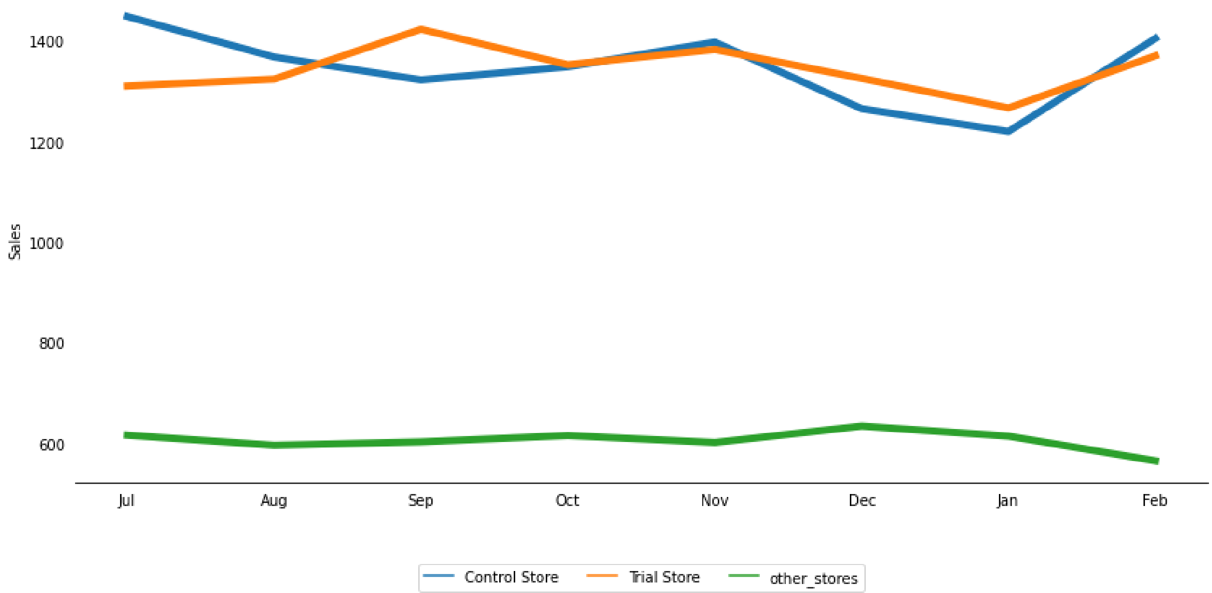


The trend of both total sales and number of customers are similar.

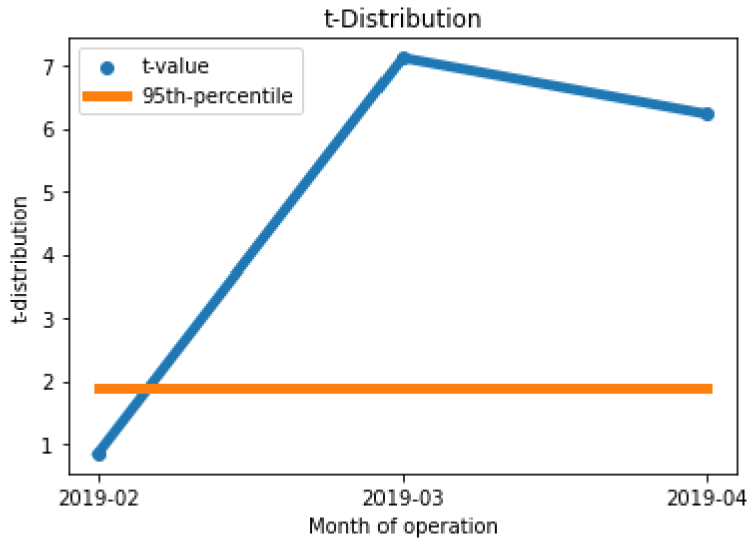
Assessment for totSales

```
Analyse('totSales',237, 88)
```

```
Conclusion: There is a statistically significant difference between trial and
```

	STORE_NBR	YEARMONTH	percentageDiff	t-value	95th-percentile

Download



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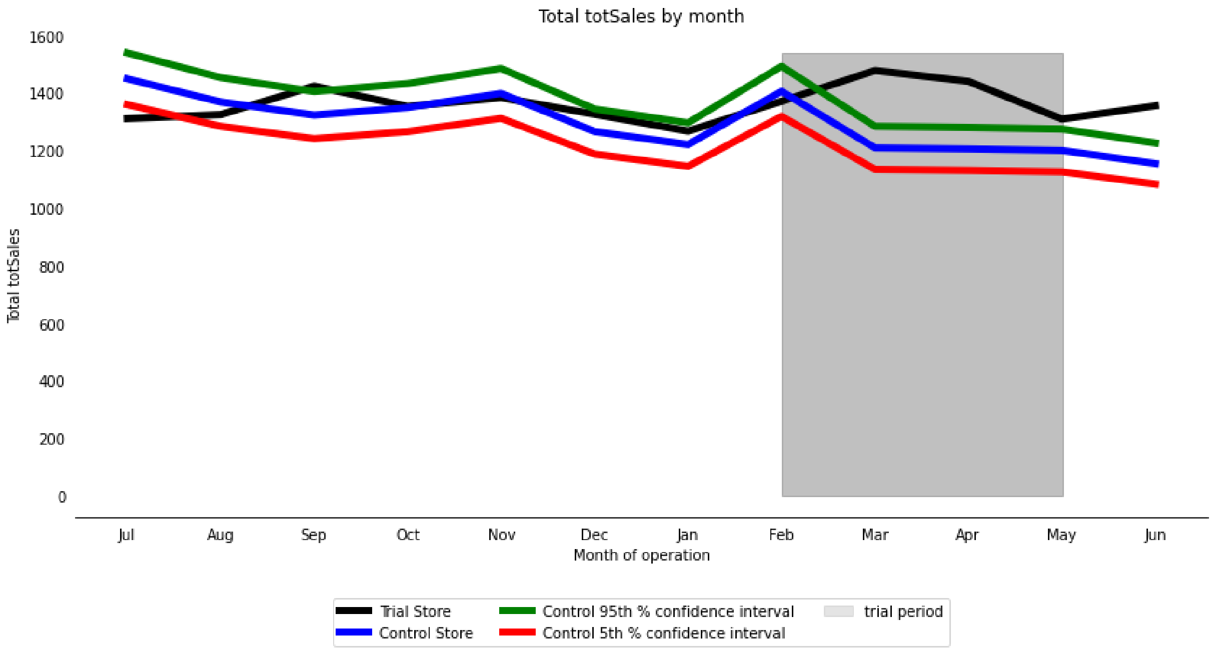


The total sales in store 88 is significantly different to its control store in the trial period as the trial store performance lies above the 95% percentile t-distribution of the control store in two of the three trial months.

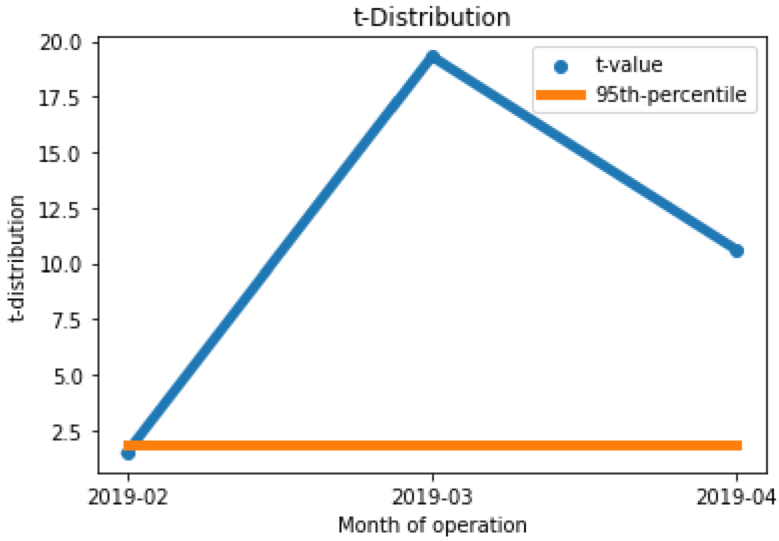
Assessment for nCustomers

```
Analyse('nCustomers',237, 88)
```

```
Conclusion: There is a statistically significant difference between trial and
```

	STORE_NBR	YEARMONTH	percentageDiff	t-value	95th-percentile

Download



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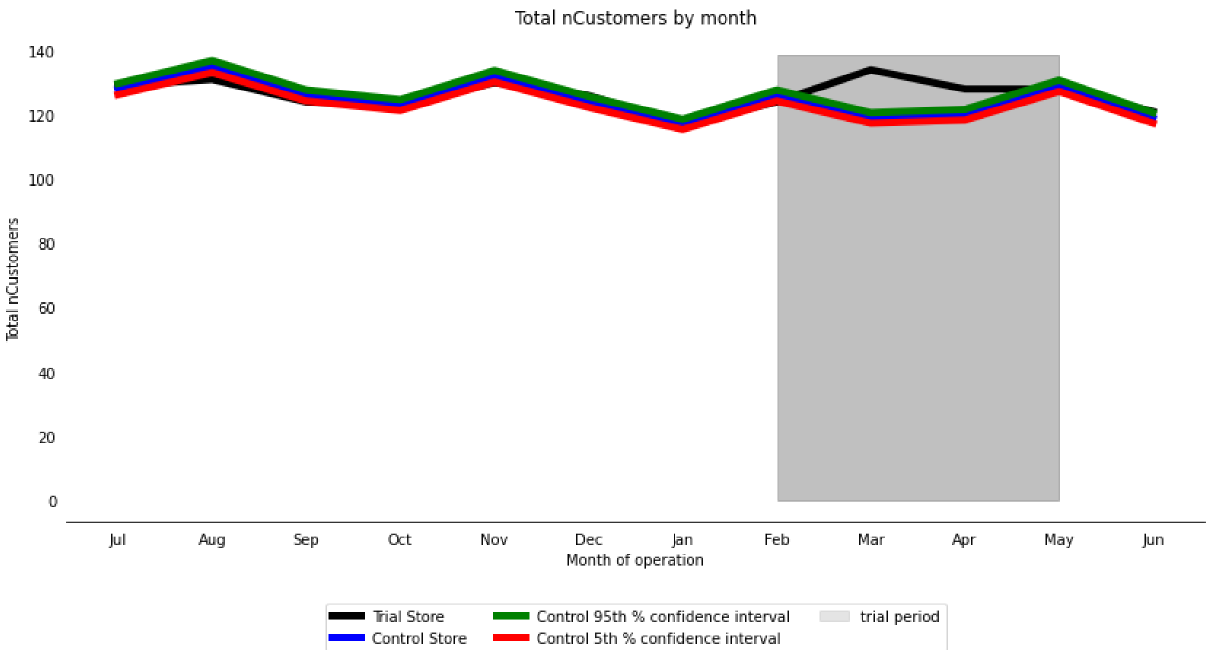

The results show that the number of customers in store 88 is significantly different to its control store in the trial period as the trial store performance lies outside of the 95% percentile the t-distribution of the control store in two of the three trial months.

Conclusion

After identifying control stores 233, 155, and 178 for trial stores 77, 86, and 88 respectively, we found that there was a significant difference in at least two of the three trial months for trial stores 77 and 88, but not for trial store 86. It may be worth checking with the client if the trial implementation was different in store 86. Overall, the trial resulted in a significant increase in sales. With the analysis completed, I prepare an executive presentation for the Category Manager