Task2_report

November 9, 2023

Task 2

[ ]:
```python
# Import libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

0.1 Load and assess the data

[ ]:
```python
# Load data
data = pd.read_csv('QVI_data.csv')
data
```

[ ]:
```
        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]
```

[ ]:
```
# Check for null values
data.isna().value_counts()
```

[ ]:
```
LYLTY_CARD_NBR  DATE   STORE_NBR  TXN_ID  PROD_NBR  PROD_NAME  PROD_QTY
TOT_SALES  PACK_SIZE  BRAND  LIFESTAGE  PREMIUM_CUSTOMER
False           False  False      False   False     False      False     False
False      False  False      False              264834
Name: count, dtype: int64
```

[ ]:
```
# Confirm dtypes
data.dtypes
```

[ ]:
```
LYLTY_CARD_NBR        int64
DATE                 object
STORE_NBR             int64
TXN_ID                int64
PROD_NBR              int64
PROD_NAME            object
PROD_QTY              int64
TOT_SALES           float64
PACK_SIZE             int64
BRAND                object
LIFESTAGE            object
PREMIUM_CUSTOMER     object
dtype: object
```

0.2 Select control stores

We will start by defining a few metrics by which we will select stores. As the trial stores need to be similar to the trial stores, we will match based on these metrics. In order to do this we will need to transform the data first.

- Create a month column in the format of yyyymm

[ ]:
```
# Convert date column to datetime
data['DATE'] = pd.to_datetime(data['DATE'])

# Add month column in the format of yyyymm
data['MONTH'] = data['DATE'].dt.strftime('%Y%m').astype(int)
data.sort_values(['STORE_NBR', 'DATE'])
```

[ ]:
```
        LYLTY_CARD_NBR       DATE  STORE_NBR  TXN_ID  PROD_NBR  \
253               1233 2018-07-01          1     266       110
547               1482 2018-07-01          1     563         8
104               1096 2018-07-02          1     110        68
430               1384 2018-07-02          1     445       106
466               1414 2018-07-02          1     482        42
…                    …          …          …       …         …
264570          272242 2019-06-25        272  269986        81
264234          272005 2019-06-26        272  269641        89
264300          272055 2019-06-28        272  269709        50
264326          272074 2019-06-30        272  269737        60
264358          272096 2019-06-30        272  269769        49

                                       PROD_NAME  PROD_QTY  TOT_SALES  \
253                WW Original Corn     Chips 200g         1        1.9
547       Smiths Crinkle Cut  Chips Original 170g         1        2.9
104           Pringles Chicken     Salt Crips 134g         1        3.7
430        Natural ChipCo      Hony Soy Chckn175g         1        3.0
466       Doritos Corn Chip Mexican Jalapeno 150g         1        3.9
…                                            …       …          …
264570           Pringles Original   Crisps 134g         2        7.4
264234    Kettle Sweet Chilli And Sour Cream 175g         2       10.8
264300           Tostitos Lightly     Salted 175g         2        8.8
264326       Kettle Tortilla ChpsFeta&Garlic 150g         2        9.2
264358   Infuzions SourCream&Herbs Veg Strws 110g         2        7.6

        PACK_SIZE       BRAND              LIFESTAGE PREMIUM_CUSTOMER   MONTH
253           200  WOOLWORTHS         YOUNG FAMILIES       Mainstream  201807
547           170      SMITHS  YOUNG SINGLES/COUPLES       Mainstream  201807
104           134    PRINGLES  OLDER SINGLES/COUPLES          Premium  201807
430           175     NATURAL  YOUNG SINGLES/COUPLES           Budget  201807
466           150     DORITOS               RETIREES       Mainstream  201807
…               …           …                      …              …       …
264570        134    PRINGLES               RETIREES       Mainstream  201906
264234        175      KETTLE         YOUNG FAMILIES           Budget  201906
264300        175    TOSTITOS               RETIREES           Budget  201906
264326        150      KETTLE  OLDER SINGLES/COUPLES           Budget  201906
264358        110   INFUZIONS         YOUNG FAMILIES       Mainstream  201906
```

```
[264834 rows x 13 columns]
```

- Aggregate the data into the monthly amounts of each column split by Store number

```
[ ]: def metric_calc():
         measure = data.groupby(['STORE_NBR', 'MONTH'])
         totSales = measure['TOT_SALES'].sum()
         nCustomers = measure['LYLTY_CARD_NBR'].nunique()
         nTxnPerCust = measure['TXN_ID'].count() / nCustomers
         nChipsPerTxn = measure['PROD_QTY'].sum() / measure['TXN_ID'].count()
         avgPricePerUnit = totSales / measure['PROD_QTY'].sum()
         aggregate = [totSales, nCustomers, nTxnPerCust, nChipsPerTxn,␣
      ↪avgPricePerUnit]
         metrics = pd.concat(aggregate, axis=1)
         metrics.columns = ['totSales', 'nCustomers', 'nTxnPerCust', 'nChipsPerTxn',␣
      ↪'avgPricePerUnit']
         return metrics
```

```
[ ]: # Create metrics dataframe
     measureOverTime = metric_calc().reset_index()

     # Sort by month
     measureOverTime = measureOverTime.sort_values(['STORE_NBR','MONTH'])

     measureOverTime
```

```
[ ]:       STORE_NBR   MONTH  totSales  nCustomers  nTxnPerCust  nChipsPerTxn  \
     0             1  201807     206.9          49     1.061224      1.192308
     1             1  201808     176.1          42     1.023810      1.255814
     2             1  201809     278.8          59     1.050847      1.209677
     3             1  201810     188.1          44     1.022727      1.288889
     4             1  201811     192.6          46     1.021739      1.212766
     …           …       …        …           …            …             …
     3164        272  201902     395.5          45     1.066667      1.895833
     3165        272  201903     442.3          50     1.060000      1.905660
     3166        272  201904     445.1          54     1.037037      1.875000
     3167        272  201905     314.6          34     1.176471      1.775000
     3168        272  201906     312.1          34     1.088235      1.891892

           avgPricePerUnit
     0            3.337097
     1            3.261111
     2            3.717333
     3            3.243103
     4            3.378947
     …                 …
```

```
3164         4.346154
3165         4.379208
3166         4.239048
3167         4.430986
3168         4.458571

[3169 rows x 7 columns]
```

- Now we can filter the data between the pre-trial data and the full observation period stores

[ ]:
```python
# Full observation data

# Find stores that were observed for the full period
observe_counts = measureOverTime['STORE_NBR'].value_counts()
observe_index = observe_counts[observe_counts == 12].index

# Filter into new dataframe with only the stores found
storesWithFullObs = measureOverTime[measureOverTime['STORE_NBR'].
 ↪isin(observe_index)]
storesWithFullObs
```

[ ]:
```
      STORE_NBR   MONTH  totSales  nCustomers  nTxnPerCust  nChipsPerTxn  \
0             1  201807     206.9          49     1.061224      1.192308
1             1  201808     176.1          42     1.023810      1.255814
2             1  201809     278.8          59     1.050847      1.209677
3             1  201810     188.1          44     1.022727      1.288889
4             1  201811     192.6          46     1.021739      1.212766
…           …       …         …           …           …             …
3164        272  201902     395.5          45     1.066667      1.895833
3165        272  201903     442.3          50     1.060000      1.905660
3166        272  201904     445.1          54     1.037037      1.875000
3167        272  201905     314.6          34     1.176471      1.775000
3168        272  201906     312.1          34     1.088235      1.891892

      avgPricePerUnit
0            3.337097
1            3.261111
2            3.717333
3            3.243103
4            3.378947
…                 …
3164         4.346154
3165         4.379208
3166         4.239048
3167         4.430986
3168         4.458571

[3120 rows x 7 columns]
```

```
[ ]: # Pre-trial data

     # Filter all stores in the full observation to only have the data before the␣
      ↪trial period
     preTrialMeasures = measureOverTime[(measureOverTime['MONTH'] < 201902) &␣
      ↪(measureOverTime['STORE_NBR'].isin(storesWithFullObs['STORE_NBR']))]
     preTrialMeasures
```

```
[ ]:       STORE_NBR   MONTH  totSales  nCustomers  nTxnPerCust  nChipsPerTxn  \
     0            1  201807     206.9          49     1.061224      1.192308
     1            1  201808     176.1          42     1.023810      1.255814
     2            1  201809     278.8          59     1.050847      1.209677
     3            1  201810     188.1          44     1.022727      1.288889
     4            1  201811     192.6          46     1.021739      1.212766
     …          …       …       …           …           …             …
     3159       272  201809     304.7          32     1.125000      1.972222
     3160       272  201810     430.6          44     1.159091      1.941176
     3161       272  201811     376.2          41     1.097561      1.933333
     3162       272  201812     403.9          47     1.000000      1.893617
     3163       272  201901     423.0          46     1.086957      1.920000

           avgPricePerUnit
     0            3.337097
     1            3.261111
     2            3.717333
     3            3.243103
     4            3.378947
     …                 …
     3159         4.291549
     3160         4.349495
     3161         4.324138
     3162         4.538202
     3163         4.406250

     [1820 rows x 7 columns]
```

Now that our data is filtered we can rank the similarity between control and trial stores

- Calculate correlation between each of the trial stores and control stores

```
[ ]: # Correlation calculation
     def calculateCorrelation(metricCol, storeComparison, inputTable =␣
      ↪preTrialMeasures):
         # Create table of the trial stores
         controlStores = inputTable[~inputTable['STORE_NBR'].isin([77, 86,␣
      ↪88])]['STORE_NBR'].unique()
         corr = pd.DataFrame()
```

```
    trialStore = inputTable[inputTable['STORE_NBR'] ==␣
↪storeComparison][metricCol].reset_index()
    for control in controlStores:
        storage_df = pd.DataFrame(columns= ['TRIAL_STORE', 'CONTROL_STORE',␣
↪'CORRELATION_SCORE'])
        control_store = inputTable[inputTable['STORE_NBR'] ==␣
↪control][metricCol].reset_index()
        storage_df['CORRELATION_SCORE'] = trialStore.corrwith(control_store,␣
↪axis=0)
        storage_df['TRIAL_STORE'] = storeComparison
        storage_df['CONTROL_STORE'] = control
        corr = pd.concat([corr, storage_df])
    corr = corr.groupby(['CONTROL_STORE']).mean().reset_index()
    corr['TRIAL_STORE'] = corr['TRIAL_STORE'].astype(int)
    return corr
```

- We can also calculate a standardised metric based on the absolute difference between the trial store's performance and each control store's performance

[ ]:
```
def calculateMagnitudeDistance(metricCol, storeComparison, inputTable =␣
↪preTrialMeasures):
    controlStores = inputTable[~inputTable['STORE_NBR'].isin([77, 86,␣
↪88])]['STORE_NBR'].unique()
    calcDistTable = pd.DataFrame()

    for control in controlStores:
        calculatedMeasure = pd.DataFrame(columns= ['MONTH', 'TRIAL_STORE',␣
↪'CONTROL_STORE', 'MEASURE'])
        calculatedMeasure['MONTH'] = list(inputTable[inputTable['STORE_NBR'] ==␣
↪storeComparison]['MONTH'])
        calculatedMeasure['TRIAL_STORE'] = storeComparison
        calculatedMeasure['CONTROL_STORE'] = control
        calculatedMeasure['MEASURE'] = abs(inputTable[inputTable['STORE_NBR']␣
↪== storeComparison].reset_index()[metricCol] -␣
↪inputTable[inputTable['STORE_NBR'] == control].reset_index()[metricCol])
        calcDistTable = pd.concat([calcDistTable, calculatedMeasure])
    return calcDistTable
```

- Now convert the measure column into an absolute value between 0 and 1 for the entire pre-trial period

[ ]:
```
# Standardize the magnitude distance
def minMaxDist(calcDistTable):
    # Calculate min and max distances by grouping by 'TRIAL_STORE' and 'MONTH'
    min_max_dist = calcDistTable.groupby(['TRIAL_STORE', 'MONTH'])['MEASURE'].
↪agg(['min', 'max']).reset_index()
    min_max_dist.columns = ['TRIAL_STORE', 'MONTH', 'minDist', 'maxDist']
```

```
    # Merge the calculated min and max distances with the original calcDistTable
    distTable = pd.merge(calcDistTable, min_max_dist, on=['TRIAL_STORE',␣
↪'MONTH'])

    # Calculate the magnitude MEASURE
    distTable['mag_measure'] = 1 - (distTable['MEASURE'] -␣
↪distTable['minDist']) / (distTable['maxDist'] - distTable['minDist'])
    finalDistTable = distTable.groupby(['CONTROL_STORE',␣
↪'TRIAL_STORE'])['mag_measure'].mean().reset_index()
    finalDistTable.convert_dtypes()
    return finalDistTable
```

Now we can put the funtions to use calculating the metrics in specificity

0.2.1 Trial Store 77 analysis

- Start with correlation of total sales and number of customers with store 77

[ ]:
```
corr_nSales = calculateCorrelation('totSales', 77)
corr_nSales
```

[ ]:
```
     CONTROL_STORE  TRIAL_STORE  CORRELATION_SCORE
0                1           77           0.537609
1                2           77           0.368461
2                3           77           0.903322
3                4           77           0.368350
4                5           77           0.444674
..             …           …                 …
252            268           77           0.672379
253            269           77           0.342135
254            270           77           0.657715
255            271           77           0.677744
256            272           77           0.558811

[257 rows x 3 columns]
```

[ ]:
```
corr_nCustomers = calculateCorrelation('nCustomers', 77)
corr_nCustomers
```

[ ]:
```
     CONTROL_STORE  TRIAL_STORE  CORRELATION_SCORE
0                1           77           0.661084
1                2           77           0.213975
2                3           77           0.917104
3                4           77           0.352181
4                5           77           0.685329
..             …           …                 …
252            268           77           0.684759
```

```
253         269       77      0.262854
254         270       77      0.434370
255         271       77      0.509815
256         272       77      0.611609

[257 rows x 3 columns]
```

- And now the magnitude for these same options

```
[ ]: magnitude_nSales = minMaxDist(calculateMagnitudeDistance('totSales', 77))
magnitude_nSales
```

```
[ ]:     CONTROL_STORE  TRIAL_STORE  mag_measure
0                1           77     0.955061
1                2           77     0.939318
2                3           77     0.354963
3                4           77     0.177414
4                5           77     0.554066
..             …           …          …
252            268           77     0.962563
253            269           77     0.452903
254            270           77     0.446991
255            271           77     0.553304
256            272           77     0.886697

[257 rows x 3 columns]
```

```
[ ]: magnitude_nCustomers = minMaxDist(calculateMagnitudeDistance('nCustomers', 77))
magnitude_nCustomers
```

```
[ ]:     CONTROL_STORE  TRIAL_STORE  mag_measure
0                1           77     0.940321
1                2           77     0.924638
2                3           77     0.345067
3                4           77     0.189579
4                5           77     0.481199
..             …           …          …
252            268           77     0.939907
253            269           77     0.343547
254            270           77     0.357725
255            271           77     0.483457
256            272           77     0.948207

[257 rows x 3 columns]
```

- We shall now create a function to merge the magnitude and correlation tables

[ ]:
```
def merge_calcs(metricCol, storeComparison):
    corr = calculateCorrelation(metricCol, storeComparison)
    magnitude = minMaxDist(calculateMagnitudeDistance(metricCol,␣
 ↪storeComparison))
    combine = corr.merge(magnitude, on=['TRIAL_STORE', 'CONTROL_STORE'])
    combine['Merged_Score'] = 0.5 * combine['CORRELATION_SCORE'] + 0.5 *␣
 ↪combine['mag_measure']
    return combine
```

- Now test the function by merging sales and customer scores

[ ]:
```
scoreNSales = merge_calcs(['totSales'], 77)
scoreNSales
```

[ ]:

	CONTROL_STORE	TRIAL_STORE	CORRELATION_SCORE	mag_measure	Merged_Score
0	1	77	0.537609	0.955061	0.746335
1	2	77	0.368461	0.939318	0.653889
2	3	77	0.903322	0.354963	0.629143
3	4	77	0.368350	0.177414	0.272882
4	5	77	0.444674	0.554066	0.499370
..	…	…	…	…	…
252	268	77	0.672379	0.962563	0.817471
253	269	77	0.342135	0.452903	0.397519
254	270	77	0.657715	0.446991	0.552353
255	271	77	0.677744	0.553304	0.615524
256	272	77	0.558811	0.886697	0.722754

[257 rows x 5 columns]

[ ]:
```
scoreNCustomers = merge_calcs('nCustomers', 77)
scoreNCustomers
```

[ ]:

	CONTROL_STORE	TRIAL_STORE	CORRELATION_SCORE	mag_measure	Merged_Score
0	1	77	0.661084	0.940321	0.800702
1	2	77	0.213975	0.924638	0.569306
2	3	77	0.917104	0.345067	0.631085
3	4	77	0.352181	0.189579	0.270880
4	5	77	0.685329	0.481199	0.583264
..	…	…	…	…	…
252	268	77	0.684759	0.939907	0.812333
253	269	77	0.262854	0.343547	0.303200
254	270	77	0.434370	0.357725	0.396048
255	271	77	0.509815	0.483457	0.496636
256	272	77	0.611609	0.948207	0.779908

[257 rows x 5 columns]

With the functions working to calculated based on an individual driver, and the tables already generated for Sales and customer, we can move onto the next step.

- Combine the generated scores together to create a new average score table

[ ]:
```
scoreControl = scoreNSales.merge(scoreNCustomers, on= ['TRIAL_STORE',␣
↪'CONTROL_STORE'])
scoreControl['Final_Score'] = 0.5 * scoreControl['Merged_Score_x'] + 0.5 *␣
↪scoreControl['Merged_Score_y']
scoreControl
```

[ ]:
```
     CONTROL_STORE  TRIAL_STORE  CORRELATION_SCORE_x  mag_measure_x  \
0                1           77             0.537609       0.955061
1                2           77             0.368461       0.939318
2                3           77             0.903322       0.354963
3                4           77             0.368350       0.177414
4                5           77             0.444674       0.554066
..             …          …                  …            …
252            268           77             0.672379       0.962563
253            269           77             0.342135       0.452903
254            270           77             0.657715       0.446991
255            271           77             0.677744       0.553304
256            272           77             0.558811       0.886697

     Merged_Score_x  CORRELATION_SCORE_y  mag_measure_y  Merged_Score_y  \
0          0.746335             0.661084       0.940321        0.800702
1          0.653889             0.213975       0.924638        0.569306
2          0.629143             0.917104       0.345067        0.631085
3          0.272882             0.352181       0.189579        0.270880
4          0.499370             0.685329       0.481199        0.583264
..              …                  …            …             …
252        0.817471             0.684759       0.939907        0.812333
253        0.397519             0.262854       0.343547        0.303200
254        0.552353             0.434370       0.357725        0.396048
255        0.615524             0.509815       0.483457        0.496636
256        0.722754             0.611609       0.948207        0.779908

     Final_Score
0       0.773519
1       0.611598
2       0.630114
3       0.271881
4       0.541317
..           …
252     0.814902
253     0.350360
254     0.474200
255     0.556080
256     0.751331
```

```
[257 rows x 9 columns]
```

We can sort the dataframe by the final score column to find the highest matching store

```
[ ]: scoreControl.sort_values('Final_Score', ascending=False).head()
```

```
[ ]:      CONTROL_STORE  TRIAL_STORE  CORRELATION_SCORE_x  mag_measure_x  \
218            233           77             0.951887       0.987091
38              41           77             0.891616       0.966917
15              17           77             0.921334       0.882314
238            254           77             0.788554       0.924468
105            115           77             0.844579       0.934576

     Merged_Score_x  CORRELATION_SCORE_y  mag_measure_y  Merged_Score_y  \
218        0.969489             0.995179       0.992773        0.993976
38         0.929267             0.922110       0.974639        0.948374
15         0.901824             0.873654       0.962495        0.918075
238        0.856511             0.958104       0.937131        0.947618
105        0.889578             0.859441       0.965916        0.912678

     Final_Score
218     0.981733
38      0.938821
15      0.909949
238     0.902064
105     0.901128
```

The store with the highest final score, and therefore the closest to the selected trial store, is Store 233. Now that we have found a control store, let's visually check if the drivers are indeed similar in the period before the trial.

- We will first filter the driver data for the stores

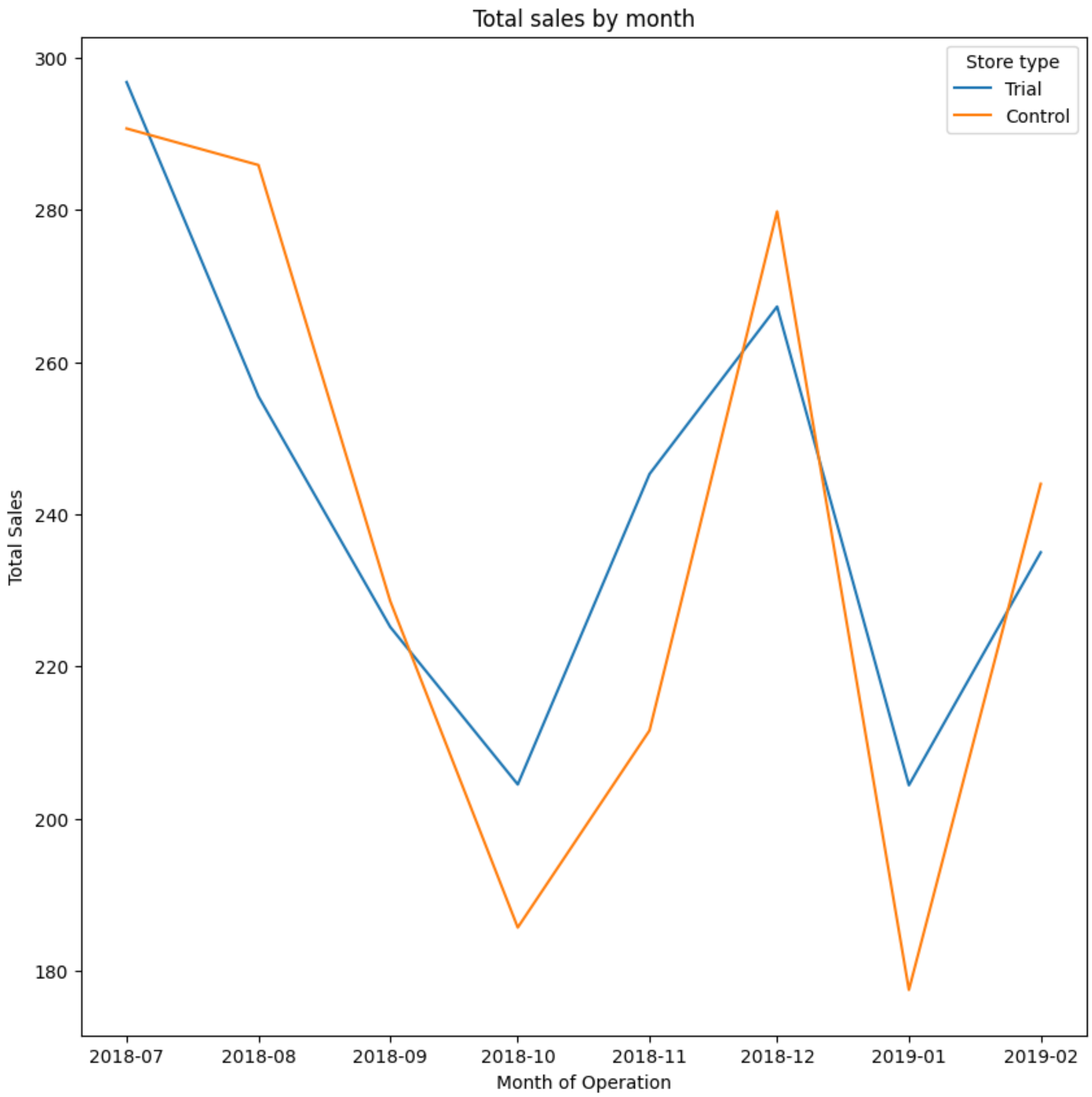
```
[ ]: # Filter the measureOverTime dataframe for only the control and trial stores
pastSales = measureOverTime[(measureOverTime['STORE_NBR']==77) |␣
 ↪(measureOverTime['STORE_NBR']==233)].copy()
pastSales['Store_type'] = pastSales.apply(
                                                   lambda row: 'Trial' if␣
 ↪row['STORE_NBR'] == 77
                                                   else 'Control',
                                                   axis=1
                                               )
pastSales['TransactionMonth'] = pd.to_datetime(pastSales['MONTH'],␣
 ↪format='%Y%m')
pastSales = pastSales[pastSales['MONTH'] < 201903]
pastSales.head()
```

[ ]:
```
     STORE_NBR   MONTH  totSales  nCustomers  nTxnPerCust  nChipsPerTxn  \
880         77  201807     296.8          51     1.078431      1.527273
881         77  201808     255.5          47     1.021277      1.541667
882         77  201809     225.2          42     1.047619      1.590909
883         77  201810     204.5          37     1.027027      1.368421
884         77  201811     245.3          41     1.073171      1.522727

     avgPricePerUnit Store_type TransactionMonth
880         3.533333      Trial       2018-07-01
881         3.452703      Trial       2018-08-01
882         3.217143      Trial       2018-09-01
883         3.932692      Trial       2018-10-01
884         3.661194      Trial       2018-11-01
```

- Next we will plot the total sales for both stores to visually compare them

[ ]:
```python
# Plot graph
plt.figure(figsize=(10,10))
sns.lineplot(pastSales, x='TransactionMonth', y='totSales', hue='Store_type')
plt.xlabel('Month of Operation')
plt.ylabel('Total Sales')
plt.title('Total sales by month')
plt.legend(title= 'Store type')
```

[ ]:
```
<matplotlib.legend.Legend at 0x7f921cff14d0>
```



- We will do the same for customers

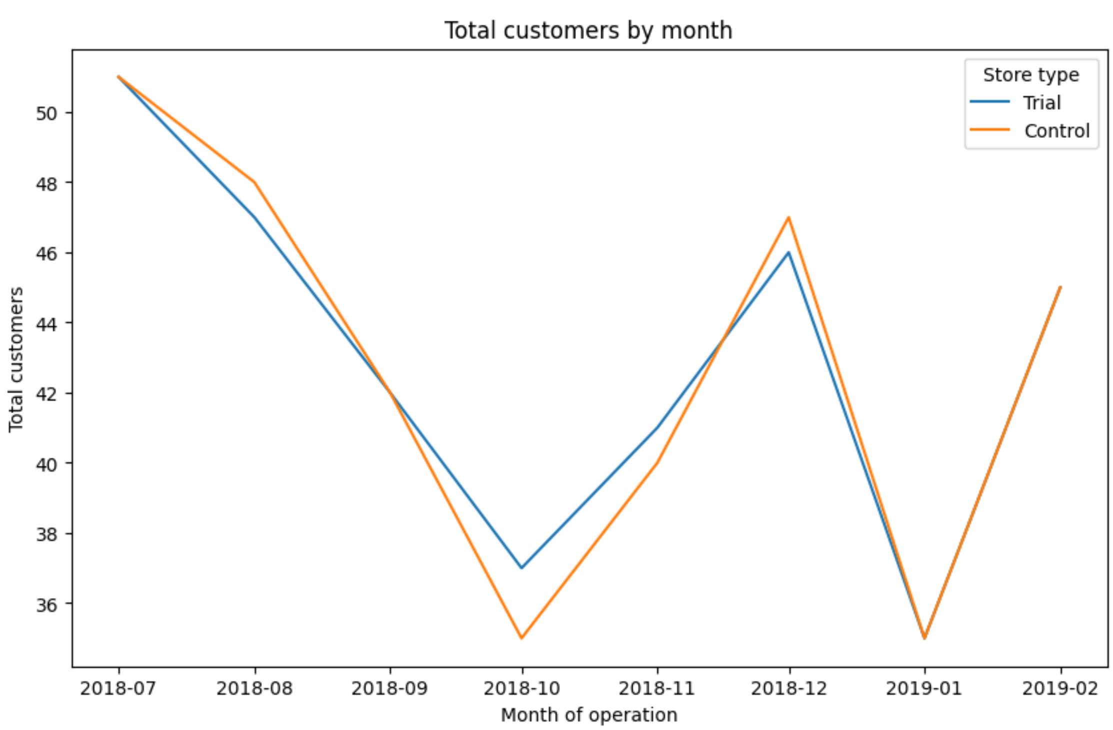
[ ]:
```
pastCustomers = measureOverTime[(measureOverTime['STORE_NBR']==77) |␣
↪(measureOverTime['STORE_NBR']==233)].copy()
pastCustomers['Store_type'] = pastCustomers.apply(
                                                lambda row: 'Trial' if␣
↪row['STORE_NBR'] == 77
                                                else 'Control',
                                                axis=1
                                            )
pastCustomers['TransactionMonth'] = pd.to_datetime(pastCustomers['MONTH'],␣
↪format='%Y%m')
pastCustomers = pastCustomers[pastCustomers['MONTH'] < 201903]
```

```
pastCustomers.head()
```

```
[ ]:      STORE_NBR   MONTH  totSales  nCustomers  nTxnPerCust  nChipsPerTxn  \
880         77  201807     296.8          51     1.078431      1.527273
881         77  201808     255.5          47     1.021277      1.541667
882         77  201809     225.2          42     1.047619      1.590909
883         77  201810     204.5          37     1.027027      1.368421
884         77  201811     245.3          41     1.073171      1.522727

     avgPricePerUnit Store_type TransactionMonth
880         3.533333      Trial       2018-07-01
881         3.452703      Trial       2018-08-01
882         3.217143      Trial       2018-09-01
883         3.932692      Trial       2018-10-01
884         3.661194      Trial       2018-11-01
```

```
[ ]: # Plot the data using Matplotlib
plt.figure(figsize=(10, 6))
sns.lineplot(pastCustomers, x='TransactionMonth', y='nCustomers',␣
 ↪hue='Store_type')
plt.xlabel('Month of operation')
plt.ylabel('Total customers')
plt.title('Total customers by month')
plt.legend(title='Store type')
```

```
[ ]: <matplotlib.legend.Legend at 0x7f92195ea250>
```



Next we will compare the results of the trial period for the trial and control stores

- Scale pre-trial control sales to match pre-trial trial store sales

```
[ ]: # Calculate scaling factor
scalingFactor = preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 77) &␣
 ↪(preTrialMeasures['MONTH'] < 201902)]['totSales'].sum() /␣
 ↪preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 233) &␣
 ↪(preTrialMeasures['MONTH'] < 201902)]['totSales'].sum()

# Apply the scaling factor
scaledControlSales = measureOverTime[measureOverTime['STORE_NBR'] == 233].copy()
scaledControlSales['controlSales'] = scaledControlSales['totSales'] *␣
 ↪scalingFactor
scaledControlSales = scaledControlSales[['MONTH', 'STORE_NBR', 'controlSales']]
scaledControlSales
```

[ ]:

	MONTH	STORE_NBR	controlSales
2699	201807	233	297.565550
2700	201808	233	292.652187
2701	201809	233	233.998916
2702	201810	233	190.085733
2703	201811	233	216.597421
2704	201812	233	286.408121
2705	201901	233	181.692071
2706	201902	233	249.762622
2707	201903	233	203.802205
2708	201904	233	162.345704
2709	201905	233	352.533799
2710	201906	233	226.219424

- Calculate the percentage difference between scaled control sales and trial sales

```
[ ]: percentagediff = pd.merge(scaledControlSales,␣
 ↪measureOverTime[measureOverTime['STORE_NBR']==77][['MONTH', 'STORE_NBR',␣
 ↪'totSales']], how='left', on='MONTH')
percentagediff['percentageDiff'] = (percentagediff['totSales'] -␣
 ↪percentagediff['controlSales'])/percentagediff['controlSales']
percentagediff
```

[ ]:

	MONTH	STORE_NBR_x	controlSales	STORE_NBR_y	totSales	percentageDiff
0	201807	233	297.565550	77	296.8	-0.002573
1	201808	233	292.652187	77	255.5	-0.126950
2	201809	233	233.998916	77	225.2	-0.037602
3	201810	233	190.085733	77	204.5	0.075830
4	201811	233	216.597421	77	245.3	0.132516

```
5   201812          233   286.408121          77    267.3        -0.066716
6   201901          233   181.692071          77    204.4         0.124980
7   201902          233   249.762622          77    235.0        -0.059107
8   201903          233   203.802205          77    278.5         0.366521
9   201904          233   162.345704          77    263.5         0.623080
10  201905          233   352.533799          77    299.3        -0.151003
11  201906          233   226.219424          77    264.7         0.170103
```

- Calculate the standard deviation for the percentage difference between sales over the period

[ ]:
```
stdDev = percentagediff[percentagediff['MONTH'] < 201902]['percentageDiff'].
↪std()
stdDev
```

[ ]:
```
0.09958646884078388
```

- Calculate the t-values of the trial months

[ ]:
```
percentagediff['tValue'] = (percentagediff[(percentagediff['MONTH'] >= 201902)␣
↪& (percentagediff['MONTH'] <= 201904)]['percentageDiff'] -␣
↪percentagediff['percentageDiff'].mean()) / stdDev
trialTable = percentagediff[(percentagediff['MONTH'] >= 201902) &␣
↪(percentagediff['MONTH'] <= 201904)]
trialTable
```

[ ]:
```
    MONTH  STORE_NBR_x  controlSales  STORE_NBR_y  totSales  percentageDiff  \
7  201902          233    249.762622           77     235.0       -0.059107
8  201903          233    203.802205           77     278.5        0.366521
9  201904          233    162.345704           77     263.5        0.623080

     tValue
7 -1.471383
8  2.802568
9  5.378807
```

- Find the 95th percentile of the t distribution with the appropriate degree of freedom

[ ]:
```
from scipy.stats import t
# Set degrees of freedom
degreesOfFreedom = 7
# Calculate percentile
p = t.ppf(0.95, df=degreesOfFreedom)
print(f'The 95th percentile of the t-distribution is {p}')
```

```
The 95th percentile of the t-distribution is 1.894578605061305
```

We can observe that the t-values for March and April are much larger the the 95th percentile of the distribution. This means that the increase in sales in the trial store in March and April are significantly greater than that in the control store.

Let's visualize this by plotting the sales and the 95th percentile value of the stores for the trial period.

- Filter data for the 2 stores total sales, and the 95th and 5th percentiles of the control store sales

[ ]:
```
# Filter the measureOverTime dataframe for only the control and trial stores
pastSales = measureOverTime[(measureOverTime['STORE_NBR']==77) |␣
↪(measureOverTime['STORE_NBR']==233)].copy()
pastSales['Store_type'] = pastSales.apply(
                                                    lambda row: 'Trial' if␣
↪row['STORE_NBR'] == 77
                                                    else 'Control',
                                                    axis=1
                                                )
pastSales['TransactionMonth'] = pd.to_datetime(pastSales['MONTH'],␣
↪format='%Y%m')
pastSales = pastSales[(pastSales['MONTH'] >= 201902) & (pastSales['MONTH'] <=␣
↪201904)]
# Create new dataframe with the totSales of control store set to 95th percentile
pastSales_Controls95 = pastSales[pastSales['Store_type'] == 'Control'].copy()
pastSales_Controls95['totSales'] = pastSales_Controls95['totSales'] * (1 +␣
↪stdDev * 2)
pastSales_Controls95['Store_type'] = 'Control 95th % confidence interval'

# Create new dataframe with the totSales of control store set to 5th percentile
pastSales_Controls5 = pastSales[pastSales['Store_type'] == 'Control'].copy()
pastSales_Controls5['totSales'] = pastSales_Controls5['totSales'] * (1 - stdDev␣
↪* 2)
pastSales_Controls5['Store_type'] = 'Control 5th % confidence interval'

# Concat the 3 new dataframes together
trialAssessment = pd.concat([pastSales, pastSales_Controls95,␣
↪pastSales_Controls5])
trialAssessment
```

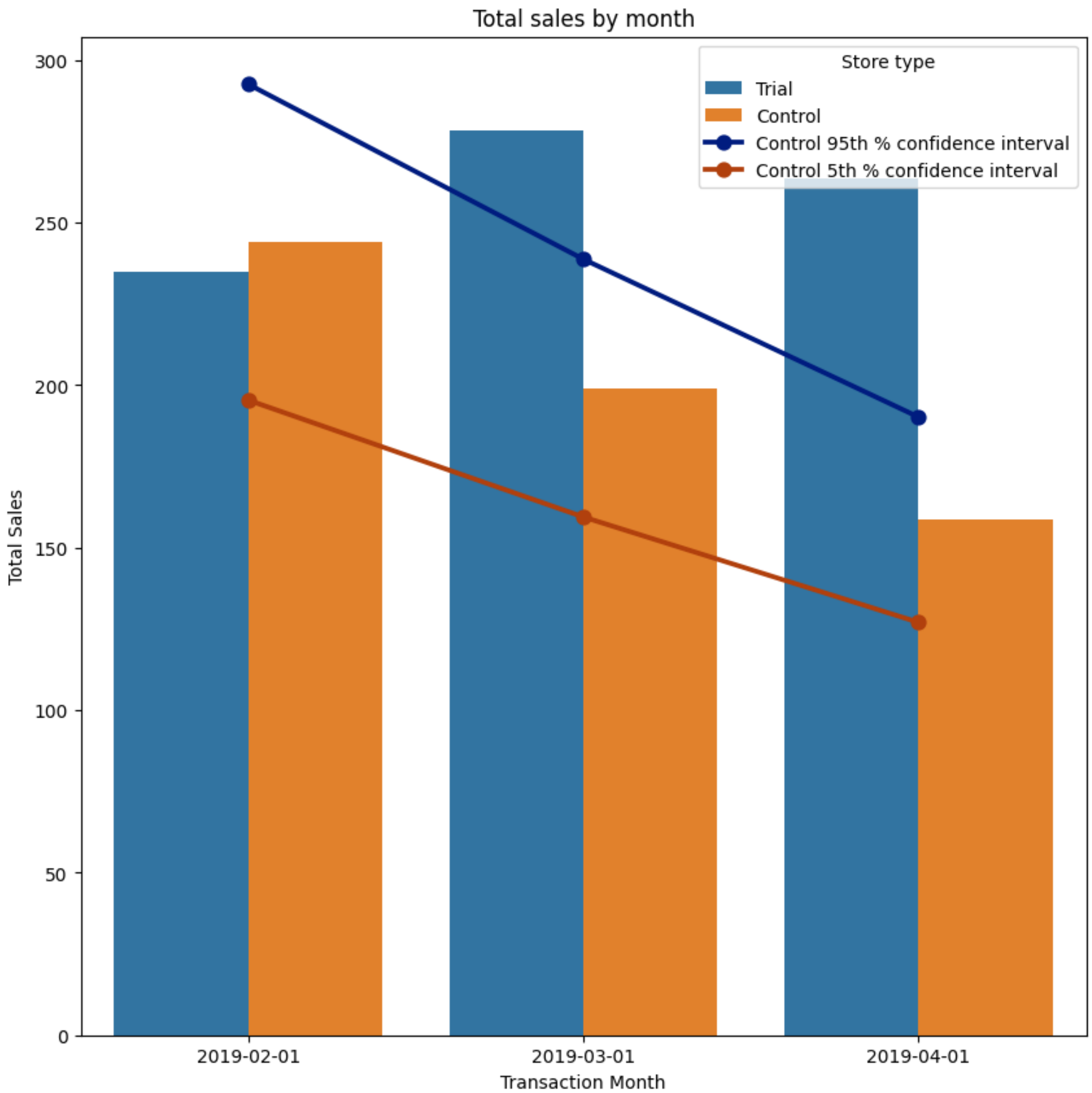
[ ]:

	STORE_NBR	MONTH	totSales	nCustomers	nTxnPerCust	nChipsPerTxn	\
887	77	201902	235.000000	45	1.000000	1.644444	
888	77	201903	278.500000	50	1.100000	1.490909	
889	77	201904	263.500000	47	1.021277	1.625000	
2706	233	201902	244.000000	45	1.044444	1.489362	
2707	233	201903	199.100000	40	1.025000	1.439024	
2708	233	201904	158.600000	30	1.100000	1.393939	
2706	233	201902	292.598197	45	1.044444	1.489362	
2707	233	201903	238.755332	40	1.025000	1.439024	
2708	233	201904	190.188828	30	1.100000	1.393939	
2706	233	201902	195.401803	45	1.044444	1.489362	

```
2707         233  201903  159.444668          40      1.025000       1.439024
2708         233  201904  127.011172          30      1.100000       1.393939

      avgPriceperUnit                         Store_type TransactionMonth
887          3.175676                              Trial       2019-02-01
888          3.396341                              Trial       2019-03-01
889          3.378205                              Trial       2019-04-01
2706         3.485714                            Control       2019-02-01
2707         3.374576                            Control       2019-03-01
2708         3.447826                            Control       2019-04-01
2706         3.485714  Control 95th % confidence interval       2019-02-01
2707         3.374576  Control 95th % confidence interval       2019-03-01
2708         3.447826  Control 95th % confidence interval       2019-04-01
2706         3.485714   Control 5th % confidence interval       2019-02-01
2707         3.374576   Control 5th % confidence interval       2019-03-01
2708         3.447826   Control 5th % confidence interval       2019-04-01
```

[ ]:
```
bar = trialAssessment[(trialAssessment['Store_type'] == 'Control') |␣
 ↪(trialAssessment['Store_type'] == 'Trial')]
line = trialAssessment[~((trialAssessment['Store_type'] == 'Control') |␣
 ↪(trialAssessment['Store_type'] == 'Trial'))]

fig, ax = plt.subplots(figsize=(10,10))

sns.barplot(data=bar, x='TransactionMonth', y='totSales', hue='Store_type',␣
 ↪ax=ax)
sns.pointplot(data=line, x='TransactionMonth', y='totSales', hue='Store_type',␣
 ↪ax=ax, palette='dark')
plt.xlabel('Transaction Month')
plt.ylabel('Total Sales')
plt.legend(title='Store type')
plt.title('Total sales by month')
```

[ ]:
```
Text(0.5, 1.0, 'Total sales by month')
```



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.

Let us now look at this assessment for the number of customers as well. We will be repeating the process from above and only displaying the outputs relevant to our analysis

```
[ ]: # Calculate scaling factor
scalingFactor = preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 77) &␣
  ↪(preTrialMeasures['MONTH'] < 201902)]['nCustomers'].sum() /␣
  ↪preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 233) &␣
  ↪(preTrialMeasures['MONTH'] < 201902)]['nCustomers'].sum()
```

```
# Apply the scaling factor
scaledControlCustomers = measureOverTime[measureOverTime['STORE_NBR'] == 233].
↪copy()
scaledControlCustomers['controlCustomers'] = ␣
↪scaledControlCustomers['nCustomers'] * scalingFactor
scaledControlCustomers = scaledControlCustomers[['MONTH', 'STORE_NBR',␣
↪'controlCustomers']]

# Calculate the percentage difference between the trial and scaled control␣
↪values
percentagediff = pd.merge(scaledControlCustomers,␣
↪measureOverTime[measureOverTime['STORE_NBR']==77][['MONTH', 'STORE_NBR',␣
↪'nCustomers']], how='left', on='MONTH')
percentagediff['percentageDiff'] = (percentagediff['nCustomers'] -␣
↪percentagediff['controlCustomers'])/percentagediff['controlCustomers']

# Calculate the standard deviation
stdDev = percentagediff[percentagediff['MONTH'] < 201902]['percentageDiff'].
↪std()
```

- Calculate the t-values of the customer amounts

```
[ ]: percentagediff['tValue'] = (percentagediff[(percentagediff['MONTH'] >= 201902)␣
↪& (percentagediff['MONTH'] <= 201904)]['percentageDiff'] -␣
↪percentagediff['percentageDiff'].mean()) / stdDev
trialTable = percentagediff[(percentagediff['MONTH'] >= 201902) &␣
↪(percentagediff['MONTH'] <= 201904)]
trialTable
```

```
[ ]:     MONTH  STORE_NBR_x  controlCustomers  STORE_NBR_y  nCustomers  \
    7  201902          233         45.151007           77          45
    8  201903          233         40.134228           77          50
    9  201904          233         30.100671           77          47

       percentageDiff     tValue
    7       -0.003344  -2.486836
    8        0.245819   6.593494
    9        0.561427  18.095245
```

- Find the 95th percentile of the t distribution with the appropriate degree of freedom

```
[ ]: from scipy.stats import t
# Set degrees of freedom
degreesOfFreedom = 7
# Calculate percentile
p = t.ppf(0.95, df=degreesOfFreedom)
print(f'The 95th percentile of the t-distribution is {p}')
```

```
The 95th percentile of the t-distribution is 1.894578605061305
```

[ ]:
```python
# Filter the measureOverTime dataframe for only the control and trial stores
pastCustomers = measureOverTime[(measureOverTime['STORE_NBR']==77) |
 ↪(measureOverTime['STORE_NBR']==233)].copy()
pastCustomers['Store_type'] = pastCustomers.apply(
                                                  lambda row: 'Trial' if
 ↪row['STORE_NBR'] == 77
                                                  else 'Control',
                                                  axis=1
                                              )
pastCustomers['TransactionMonth'] = pd.to_datetime(pastCustomers['MONTH'],
 ↪format='%Y%m')
pastCustomers = pastCustomers[(pastCustomers['MONTH'] >= 201902) &
 ↪(pastCustomers['MONTH'] <= 201904)]

# Create new dataframe with the nCustomers of control store set to 95th
 ↪percentile
pastCustomers_Controls95 = pastCustomers[pastCustomers['Store_type'] ==
 ↪'Control'].copy()
pastCustomers_Controls95['nCustomers'] = pastCustomers_Controls95['nCustomers']
 ↪* (1 + stdDev * 2)
pastCustomers_Controls95['Store_type'] = 'Control 95th % confidence interval'

# Create new dataframe with the nCustomers of control store set to 5th
 ↪percentile
pastCustomers_Controls5 = pastCustomers[pastCustomers['Store_type'] ==
 ↪'Control'].copy()
pastCustomers_Controls5['nCustomers'] = pastCustomers_Controls5['nCustomers'] *
 ↪(1 - stdDev * 2)
pastCustomers_Controls5['Store_type'] = 'Control 5th % confidence interval'

# Concat the 3 new dataframes together
trialAssessment = pd.concat([pastCustomers, pastCustomers_Controls95,
 ↪pastCustomers_Controls5])
trialAssessment
```

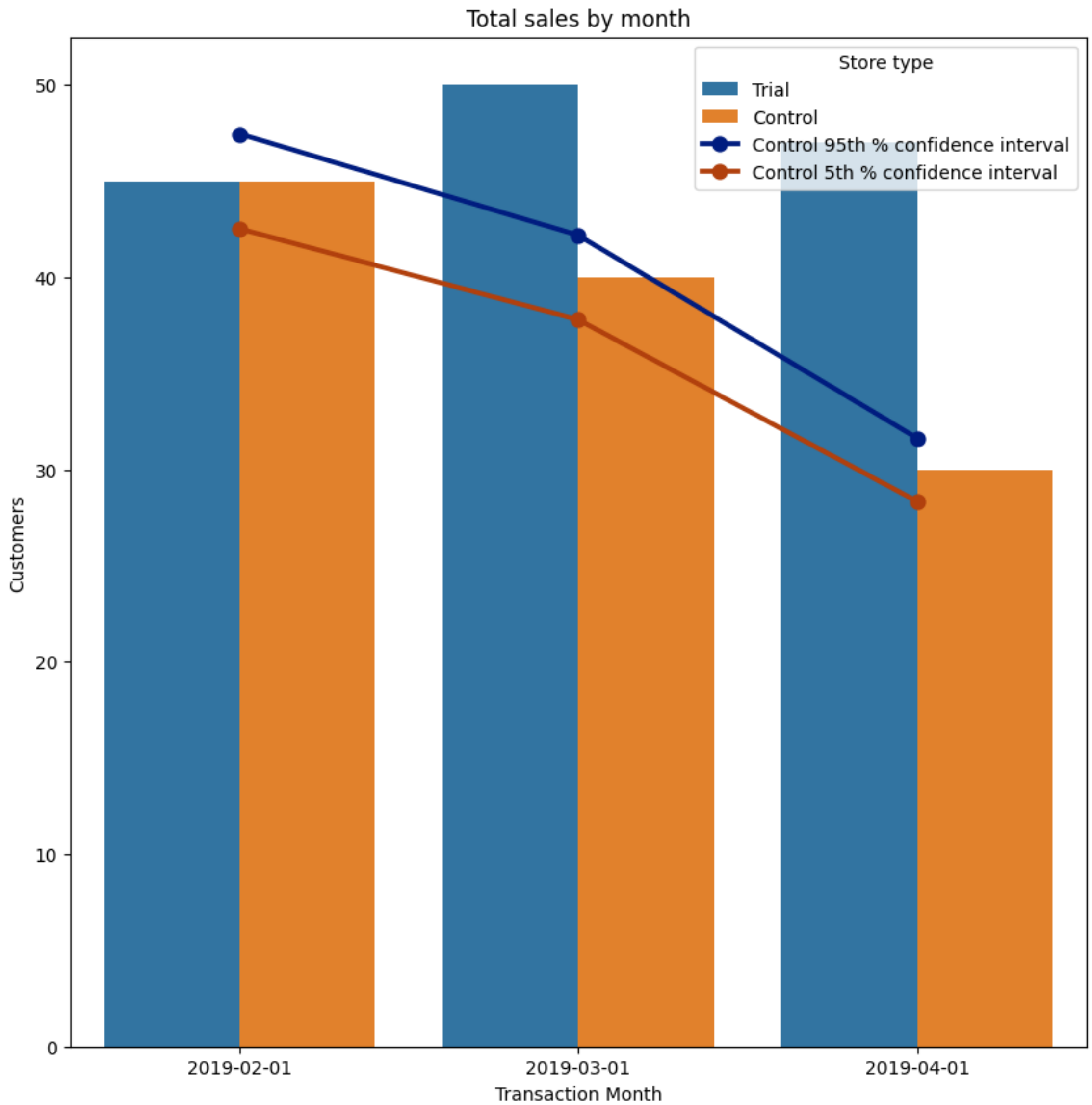
[ ]:

	STORE_NBR	MONTH	totSales	nCustomers	nTxnPerCust	nChipsPerTxn	\
887	77	201902	235.0	45.000000	1.000000	1.644444	
888	77	201903	278.5	50.000000	1.100000	1.490909	
889	77	201904	263.5	47.000000	1.021277	1.625000	
2706	233	201902	244.0	45.000000	1.044444	1.489362	
2707	233	201903	199.1	40.000000	1.025000	1.439024	
2708	233	201904	158.6	30.000000	1.100000	1.393939	
2706	233	201902	244.0	47.469596	1.044444	1.489362	
2707	233	201903	199.1	42.195197	1.025000	1.439024	
2708	233	201904	158.6	31.646398	1.100000	1.393939	

```
2706         233  201902     244.0    42.530404     1.044444     1.489362
2707         233  201903     199.1    37.804803     1.025000     1.439024
2708         233  201904     158.6    28.353602     1.100000     1.393939

      avgPricePerUnit                          Store_type TransactionMonth
887          3.175676                                Trial       2019-02-01
888          3.396341                                Trial       2019-03-01
889          3.378205                                Trial       2019-04-01
2706         3.485714                              Control       2019-02-01
2707         3.374576                              Control       2019-03-01
2708         3.447826                              Control       2019-04-01
2706         3.485714  Control 95th % confidence interval       2019-02-01
2707         3.374576  Control 95th % confidence interval       2019-03-01
2708         3.447826  Control 95th % confidence interval       2019-04-01
2706         3.485714   Control 5th % confidence interval       2019-02-01
2707         3.374576   Control 5th % confidence interval       2019-03-01
2708         3.447826   Control 5th % confidence interval       2019-04-01
```

[ ]:
```
bar = trialAssessment[(trialAssessment['Store_type'] == 'Control') |␣
 ↪(trialAssessment['Store_type'] == 'Trial')]
line = trialAssessment[~((trialAssessment['Store_type'] == 'Control') |␣
 ↪(trialAssessment['Store_type'] == 'Trial'))]

fig, ax = plt.subplots(figsize=(10,10))

sns.barplot(data=bar, x='TransactionMonth', y='nCustomers', hue='Store_type')
sns.pointplot(data=line, x='TransactionMonth', y='nCustomers',␣
 ↪hue='Store_type', palette='dark')
plt.xlabel('Transaction Month')
plt.ylabel('Customers')
plt.legend(title='Store type')
plt.title('Total sales by month')
```

[ ]:
```
Text(0.5, 1.0, 'Total sales by month')
```



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.

We can now use the same method as before to identify the most suitable control store and assess the impact of the trial on the trial stores. The next trial store to examine will be store 86

0.2.2 Trial Store 86 analysis

- Calculate the correlation scores for each store with trial store 86 for drivers total sales and customers.

[ ]:
```
# Sales correlation
corr_nSales = calculateCorrelation('totSales', 86)
corr_nSales
```

[ ]:
```
     CONTROL_STORE  TRIAL_STORE  CORRELATION_SCORE
0                1           86           0.722816
1                2           86           0.298083
2                3           86           0.369358
3                4           86           0.480482
4                5           86           0.617580
..             …            …                  …
252            268           86           0.273909
253            269           86           0.848528
254            270           86           0.134661
255            271           86           0.763819
256            272           86           0.502463

[257 rows x 3 columns]
```

[ ]:
```
# Customers correlation
corr_nCustomers = calculateCorrelation('nCustomers', 86)
corr_nCustomers
```

[ ]:
```
     CONTROL_STORE  TRIAL_STORE  CORRELATION_SCORE
0                1           86           0.742916
1                2           86           0.456920
2                3           86           0.323107
3                4           86           0.415196
4                5           86           0.373385
..             …            …                  …
252            268           86           0.482863
253            269           86           0.450707
254            270           86           0.116366
255            271           86           0.633696
256            272           86           0.323092

[257 rows x 3 columns]
```

- Next calculate and create tables for the magnitude distance for the drivers between store 86 and the other stores

[ ]:
```
magnitude_nSales = minMaxDist(calculateMagnitudeDistance('totSales', 86))
magnitude_nSales
```

[ ]:
```
     CONTROL_STORE  TRIAL_STORE  mag_measure
0                1           86     0.220565
1                2           86     0.179640
2                3           86     0.762894
```

```
3                    4           86     0.498526
4                    5           86     0.929321
..                 …           …        …
252                268           86     0.250819
253                269           86     0.902040
254                270           86     0.834520
255                271           86     0.922919
256                272           86     0.446702

[257 rows x 3 columns]
```

[ ]:
```
magnitude_nCustomers = minMaxDist(calculateMagnitudeDistance('nCustomers', 86))
magnitude_nCustomers
```

[ ]:
```
     CONTROL_STORE  TRIAL_STORE  mag_measure
0                1           86     0.444597
1                2           86     0.380620
2                3           86     0.911850
3                4           86     0.773922
4                5           86     0.926509
..             …           …        …
252            268           86     0.427390
253            269           86     0.917082
254            270           86     0.890489
255            271           86     0.935896
256            272           86     0.425196

[257 rows x 3 columns]
```

- The seperate tables for correlation and magnitude distance can now be merged to calculate a final score for each store

[ ]:
```
scoreNSales = merge_calcs(['totSales'], 86)
```

[ ]:
```
scoreNCustomers = merge_calcs('nCustomers', 86)
scoreNCustomers
```

[ ]:
```
     CONTROL_STORE  TRIAL_STORE  CORRELATION_SCORE  mag_measure  Merged_Score
0                1           86           0.742916     0.444597      0.593756
1                2           86           0.456920     0.380620      0.418770
2                3           86           0.323107     0.911850      0.617478
3                4           86           0.415196     0.773922      0.594559
4                5           86           0.373385     0.926509      0.649947
..             …           …              …          …           …
252            268           86           0.482863     0.427390      0.455126
253            269           86           0.450707     0.917082      0.683895
254            270           86           0.116366     0.890489      0.503427
255            271           86           0.633696     0.935896      0.784796
```

```
256            272          86          0.323092      0.425196      0.374144

[257 rows x 5 columns]
```

[ ]:
```
# Merge score tables to calculate final score
scoreControl = scoreNSales.merge(scoreNCustomers, on= ['TRIAL_STORE',␣
 ↪'CONTROL_STORE'])
scoreControl['Final_Score'] = 0.5 * scoreControl['Merged_Score_x'] + 0.5 *␣
 ↪scoreControl['Merged_Score_y']
scoreControl
```

[ ]:
```
     CONTROL_STORE  TRIAL_STORE  CORRELATION_SCORE_x  mag_measure_x  \
0                1           86             0.722816       0.220565
1                2           86             0.298083       0.179640
2                3           86             0.369358       0.762894
3                4           86             0.480482       0.498526
4                5           86             0.617580       0.929321
..             …          …                 …             …
252            268           86             0.273909       0.250819
253            269           86             0.848528       0.902040
254            270           86             0.134661       0.834520
255            271           86             0.763819       0.922919
256            272           86             0.502463       0.446702

     Merged_Score_x  CORRELATION_SCORE_y  mag_measure_y  Merged_Score_y  \
0          0.471691             0.742916       0.444597        0.593756
1          0.238861             0.456920       0.380620        0.418770
2          0.566126             0.323107       0.911850        0.617478
3          0.489504             0.415196       0.773922        0.594559
4          0.773450             0.373385       0.926509        0.649947
..              …                  …             …             …
252        0.262364             0.482863       0.427390        0.455126
253        0.875284             0.450707       0.917082        0.683895
254        0.484590             0.116366       0.890489        0.503427
255        0.843369             0.633696       0.935896        0.784796
256        0.474583             0.323092       0.425196        0.374144

     Final_Score
0       0.532723
1       0.328816
2       0.591802
3       0.542032
4       0.711699
..           …
252     0.358745
253     0.779589
254     0.494009
```

```
255      0.814082
256      0.424363

[257 rows x 9 columns]
```

[ ]:
```
# Sort score table to find the closest matching store
scoreControl.sort_values('Final_Score', ascending=False).head()
```

[ ]:
```
     CONTROL_STORE  TRIAL_STORE  CORRELATION_SCORE_x  mag_measure_x  \
144            155           86             0.938941       0.964782
99             109           86             0.894150       0.963810
104            114           86             0.867208       0.921021
127            138           86             0.879932       0.925434
210            225           86             0.808766       0.958060

     Merged_Score_x  CORRELATION_SCORE_y  mag_measure_y  Merged_Score_y  \
144        0.951861             0.971438       0.985037        0.978238
99         0.928980             0.885389       0.965940        0.925664
104        0.894114             0.927670       0.935508        0.931589
127        0.902683             0.874850       0.928031        0.901441
210        0.883413             0.866896       0.967367        0.917131

     Final_Score
144     0.965049
99      0.927322
104     0.912852
127     0.902062
210     0.900272
```

The store with the highest final score, and therefore the closest to the selected trial store, is Store 155. Now that we have found a control store, let's visually check if the drivers are indeed similar in the period before the trial.

- We will first filter the driver data for the stores

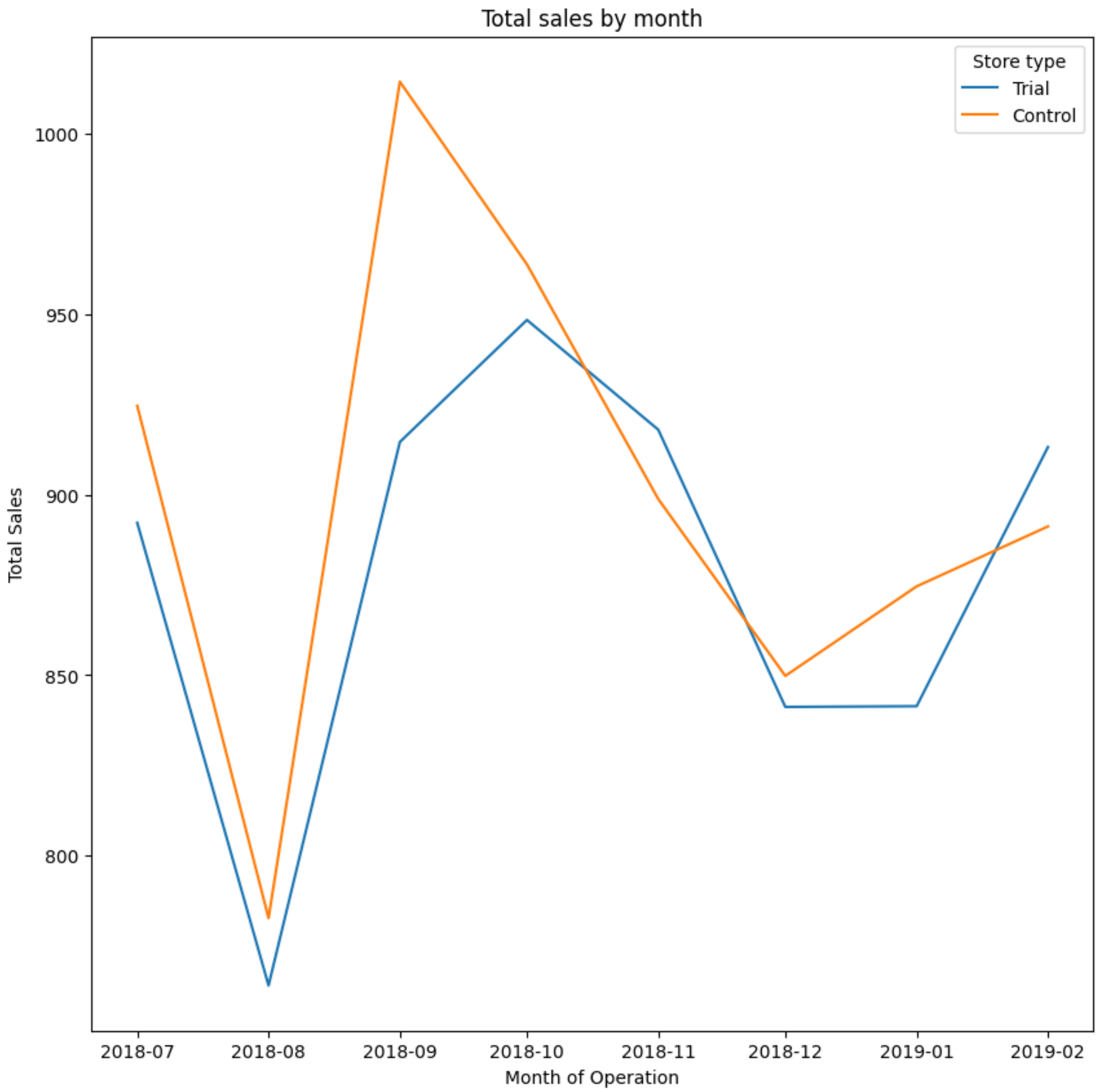
[ ]:
```
# Filter the measureOverTime dataframe for only the control and trial stores
pastSales = measureOverTime[(measureOverTime['STORE_NBR']==86) |␣
 ↪(measureOverTime['STORE_NBR']==155)].copy()
pastSales['Store_type'] = pastSales.apply(
                                                lambda row: 'Trial' if␣
 ↪row['STORE_NBR'] == 86
                                                else 'Control',
                                                axis=1
                                             )
pastSales['TransactionMonth'] = pd.to_datetime(pastSales['MONTH'],␣
 ↪format='%Y%m')
pastSales = pastSales[pastSales['MONTH'] < 201903]
pastSales.head()
```

```
[ ]:      STORE_NBR   MONTH  totSales  nCustomers  nTxnPerCust  nChipsPerTxn  \
     977         86  201807    892.20          99     1.272727      1.992063
     978         86  201808    764.05          94     1.191489      1.919643
     979         86  201809    914.60         103     1.252427      2.000000
     980         86  201810    948.40         109     1.266055      2.000000
     981         86  201811    918.00         100     1.270000      2.000000

          avgPricePerUnit Store_type TransactionMonth
     977         3.554582      Trial       2018-07-01
     978         3.553721      Trial       2018-08-01
     979         3.544961      Trial       2018-09-01
     980         3.436232      Trial       2018-10-01
     981         3.614173      Trial       2018-11-01
```

- Next we will plot the total sales for both stores to visually compare them

```
[ ]: # Plot graph
     plt.figure(figsize=(10,10))
     sns.lineplot(pastSales, x='TransactionMonth', y='totSales', hue='Store_type')
     plt.xlabel('Month of Operation')
     plt.ylabel('Total Sales')
     plt.title('Total sales by month')
     plt.legend(title= 'Store type')
```

```
[ ]: <matplotlib.legend.Legend at 0x7f92188f8b10>
```



- We will do the same for customers

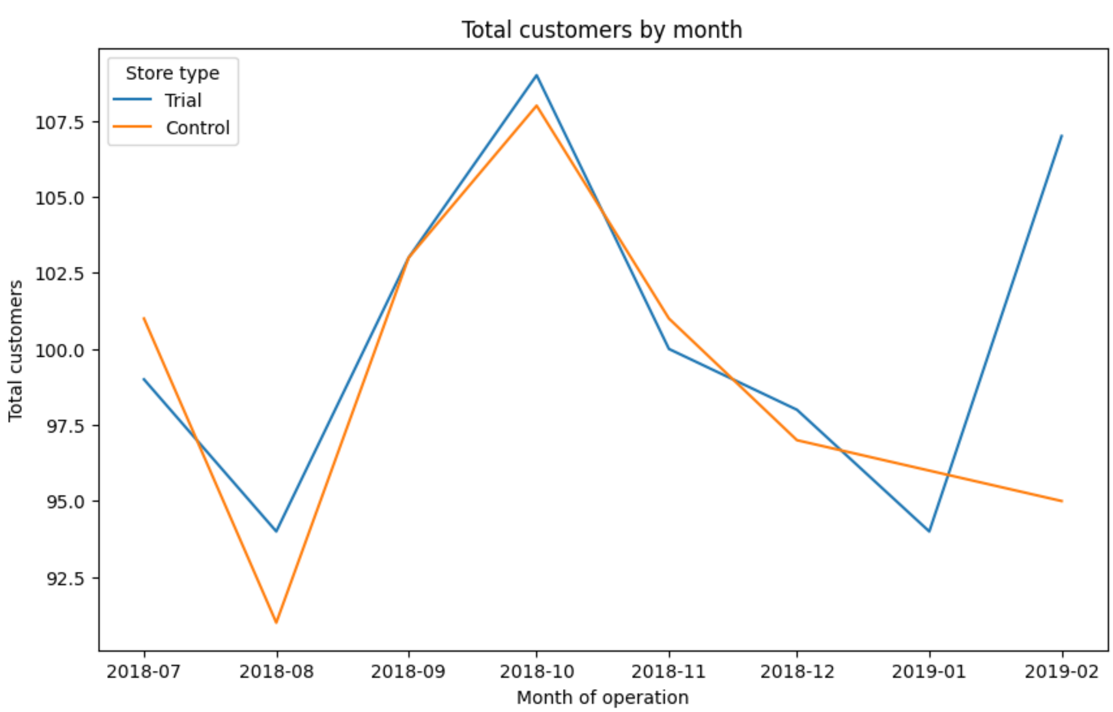
```
[ ]: pastCustomers = measureOverTime[(measureOverTime['STORE_NBR']==86) |␣
       ↪(measureOverTime['STORE_NBR']==155)].copy()
     pastCustomers['Store_type'] = pastCustomers.apply(
                                                        lambda row: 'Trial' if␣
       ↪row['STORE_NBR'] == 86
                                                        else 'Control',
                                                        axis=1
                                                    )
     pastCustomers['TransactionMonth'] = pd.to_datetime(pastCustomers['MONTH'],␣
       ↪format='%Y%m')
     pastCustomers = pastCustomers[pastCustomers['MONTH'] < 201903]
```

```python
pastCustomers.head()
```

```
[ ]:      STORE_NBR   MONTH  totSales  nCustomers  nTxnPerCust  nChipsPerTxn  \
977           86  201807    892.20          99     1.272727      1.992063
978           86  201808    764.05          94     1.191489      1.919643
979           86  201809    914.60         103     1.252427      2.000000
980           86  201810    948.40         109     1.266055      2.000000
981           86  201811    918.00         100     1.270000      2.000000

     avgPricePerUnit Store_type TransactionMonth
977         3.554582      Trial       2018-07-01
978         3.553721      Trial       2018-08-01
979         3.544961      Trial       2018-09-01
980         3.436232      Trial       2018-10-01
981         3.614173      Trial       2018-11-01
```

```python
[ ]: # Plot the data using Matplotlib
plt.figure(figsize=(10, 6))
sns.lineplot(pastCustomers, x='TransactionMonth', y='nCustomers',␣
 ↪hue='Store_type')
plt.xlabel('Month of operation')
plt.ylabel('Total customers')
plt.legend(title='Store type')
plt.title('Total customers by month')
```

```
[ ]: Text(0.5, 1.0, 'Total customers by month')
```



Next we will compare the results of the trial period for the trial and control stores

- Scale pre-trial control sales to match pre-trial trial store sales

[ ]:
```python
# Calculate scaling factor
scalingFactor = preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 86) &␣
↪(preTrialMeasures['MONTH'] < 201902)]['totSales'].sum() /␣
↪preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 155) &␣
↪(preTrialMeasures['MONTH'] < 201902)]['totSales'].sum()

# Apply the scaling factor
scaledControlSales = measureOverTime[measureOverTime['STORE_NBR'] == 155].copy()
scaledControlSales['controlSales'] = scaledControlSales['totSales'] *␣
↪scalingFactor
scaledControlSales = scaledControlSales[['MONTH', 'STORE_NBR', 'controlSales']]
scaledControlSales
```

[ ]:

	MONTH	STORE_NBR	controlSales
1793	201807	155	896.922236
1794	201808	155	759.269991
1795	201809	155	984.034086
1796	201810	155	934.948790
1797	201811	155	871.894555
1798	201812	155	824.361363
1799	201901	155	848.418979
1800	201902	155	864.522060
1801	201903	155	780.320405
1802	201904	155	819.317024
1803	201905	155	895.224622
1804	201906	155	831.539845

- Calculate the percentage difference between scaled control sales and trial sales

[ ]:
```python
percentagediff = pd.merge(scaledControlSales,␣
↪measureOverTime[measureOverTime['STORE_NBR']==86][['MONTH', 'STORE_NBR',␣
↪'totSales']], how='left', on='MONTH')
percentagediff['percentageDiff'] = (percentagediff['totSales'] -␣
↪percentagediff['controlSales'])/percentagediff['controlSales']
percentagediff
```

[ ]:

	MONTH	STORE_NBR_x	controlSales	STORE_NBR_y	totSales	percentageDiff
0	201807	155	896.922236	86	892.20	-0.005265
1	201808	155	759.269991	86	764.05	0.006296
2	201809	155	984.034086	86	914.60	-0.070561
3	201810	155	934.948790	86	948.40	0.014387
4	201811	155	871.894555	86	918.00	0.052880

```
5   201812          155   824.361363        86    841.20      0.020426
6   201901          155   848.418979        86    841.40     -0.008273
7   201902          155   864.522060        86    913.20      0.056306
8   201903          155   780.320405        86   1026.80      0.315870
9   201904          155   819.317024        86    848.20      0.035253
10  201905          155   895.224622        86    889.30     -0.006618
11  201906          155   831.539845        86    838.00      0.007769
```

- Calculate the standard deviation for the percentage difference between sales over the period

```
[ ]: stdDev = percentagediff[percentagediff['MONTH'] < 201902]['percentageDiff'].
      ↪std()
     stdDev
```

```
[ ]: 0.03768532790008376
```

- Calculate the t-values of the trial months

```
[ ]: percentagediff['tValue'] = (percentagediff[(percentagediff['MONTH'] >= 201902)␣
      ↪& (percentagediff['MONTH'] <= 201904)]['percentageDiff'] -␣
      ↪percentagediff['percentageDiff'].mean()) / stdDev
     trialTable = percentagediff[(percentagediff['MONTH'] >= 201902) &␣
      ↪(percentagediff['MONTH'] <= 201904)]
     trialTable
```

```
[ ]:     MONTH  STORE_NBR_x  controlSales  STORE_NBR_y  totSales  percentageDiff  \
     7  201902          155    864.522060           86     913.2        0.056306
     8  201903          155    780.320405           86    1026.8        0.315870
     9  201904          155    819.317024           86     848.2        0.035253

          tValue
     7  0.568756
     8  7.456411
     9  0.010085
```

- Find the 95th percentile of the t distribution with the appropriate degree of freedom

```
[ ]: from scipy.stats import t
     # Set degrees of freedom
     degreesOfFreedom = 7
     # Calculate percentile
     p = t.ppf(0.95, df=degreesOfFreedom)
     print(f'The 95th percentile of the t-distribution is {p}')
```

```
The 95th percentile of the t-distribution is 1.894578605061305
```

Next we will compare the results of the trial period for the trial and control stores

- Scale pre-trial control sales to match pre-trial trial store sales

```
[ ]: # Calculate scaling factor
scalingFactor = preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 86) &␣
 ↪(preTrialMeasures['MONTH'] < 201902)]['totSales'].sum() /␣
 ↪preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 155) &␣
 ↪(preTrialMeasures['MONTH'] < 201902)]['totSales'].sum()

# Apply the scaling factor
scaledControlSales = measureOverTime[measureOverTime['STORE_NBR'] == 155].copy()
scaledControlSales['controlSales'] = scaledControlSales['totSales'] *␣
 ↪scalingFactor
scaledControlSales = scaledControlSales[['MONTH', 'STORE_NBR', 'controlSales']]
scaledControlSales
```

[ ]:

	MONTH	STORE_NBR	controlSales
1793	201807	155	896.922236
1794	201808	155	759.269991
1795	201809	155	984.034086
1796	201810	155	934.948790
1797	201811	155	871.894555
1798	201812	155	824.361363
1799	201901	155	848.418979
1800	201902	155	864.522060
1801	201903	155	780.320405
1802	201904	155	819.317024
1803	201905	155	895.224622
1804	201906	155	831.539845

- Calculate the percentage difference between scaled control sales and trial sales

```
[ ]: percentagediff = pd.merge(scaledControlSales,␣
 ↪measureOverTime[measureOverTime['STORE_NBR']==86][['MONTH', 'STORE_NBR',␣
 ↪'totSales']], how='left', on='MONTH')
percentagediff['percentageDiff'] = (percentagediff['totSales'] -␣
 ↪percentagediff['controlSales'])/percentagediff['controlSales']
percentagediff
```

[ ]:

	MONTH	STORE_NBR_x	controlSales	STORE_NBR_y	totSales	percentageDiff
0	201807	155	896.922236	86	892.20	-0.005265
1	201808	155	759.269991	86	764.05	0.006296
2	201809	155	984.034086	86	914.60	-0.070561
3	201810	155	934.948790	86	948.40	0.014387
4	201811	155	871.894555	86	918.00	0.052880
5	201812	155	824.361363	86	841.20	0.020426
6	201901	155	848.418979	86	841.40	-0.008273
7	201902	155	864.522060	86	913.20	0.056306
8	201903	155	780.320405	86	1026.80	0.315870
9	201904	155	819.317024	86	848.20	0.035253

```
10  201905            155    895.224622           86     889.30        -0.006618
11  201906            155    831.539845           86     838.00         0.007769
```

- Calculate the standard deviation for the percentage difference between sales over the period

```
[ ]: stdDev = percentagediff[percentagediff['MONTH'] < 201902]['percentageDiff'].
      ↪std()
     stdDev
```

```
[ ]: 0.03768532790008376
```

- Calculate the t-values of the trial months

```
[ ]: percentagediff['tValue'] = (percentagediff[(percentagediff['MONTH'] >= 201902)␣
      ↪& (percentagediff['MONTH'] <= 201904)]['percentageDiff'] -␣
      ↪percentagediff['percentageDiff'].mean()) / stdDev
     trialTable = percentagediff[(percentagediff['MONTH'] >= 201902) &␣
      ↪(percentagediff['MONTH'] <= 201904)]
     trialTable
```

```
[ ]:     MONTH  STORE_NBR_x  controlSales  STORE_NBR_y  totSales  percentageDiff  \
     7  201902          155    864.522060           86     913.2        0.056306
     8  201903          155    780.320405           86    1026.8        0.315870
     9  201904          155    819.317024           86     848.2        0.035253

          tValue
     7  0.568756
     8  7.456411
     9  0.010085
```

- Find the 95th percentile of the t distribution with the appropriate degree of freedom

```
[ ]: from scipy.stats import t
     # Set degrees of freedom
     degreesOfFreedom = 7
     # Calculate percentile
     p = t.ppf(0.95, df=degreesOfFreedom)
     print(f'The 95th percentile of the t-distribution is {p}')
```

```
The 95th percentile of the t-distribution is 1.894578605061305
```

Let's visualize this by plotting the sales and the confidence intervals of the stores for the trial period.

- Filter data for the 2 stores total sales, and the 95th and 5th percentiles of the control store sales

```
[ ]: # Filter the measureOverTime dataframe for only the control and trial stores
     pastSales = measureOverTime[(measureOverTime['STORE_NBR']==86) |␣
      ↪(measureOverTime['STORE_NBR']==155)].copy()
```

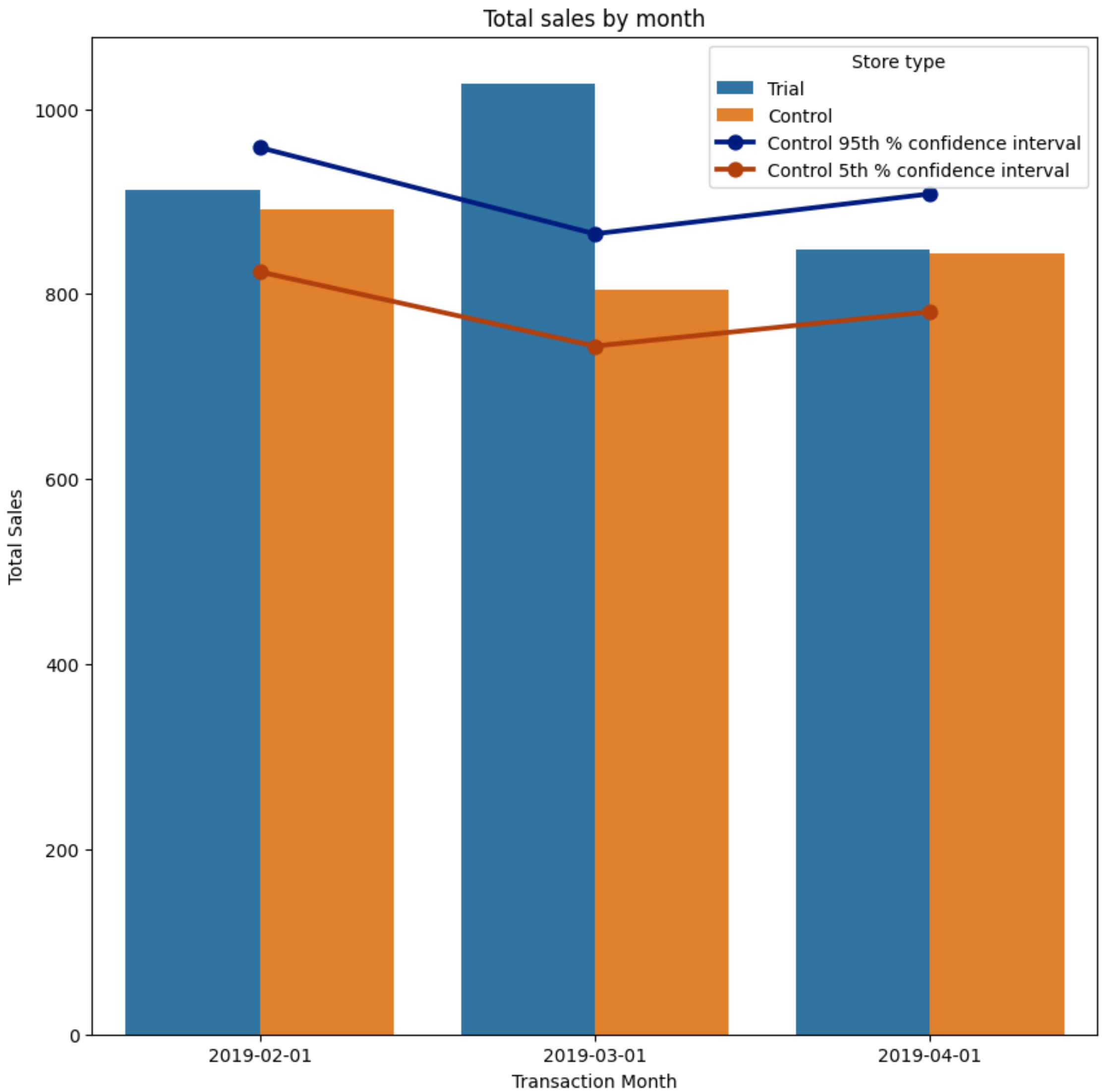
```
pastSales['Store_type'] = pastSales.apply(
                                                              lambda row: 'Trial' if␣
  ↪row['STORE_NBR'] == 86
                                                              else 'Control',
                                                              axis=1
                                                          )
pastSales['TransactionMonth'] = pd.to_datetime(pastSales['MONTH'],␣
  ↪format='%Y%m')
pastSales = pastSales[(pastSales['MONTH'] >= 201902) & (pastSales['MONTH'] <=␣
  ↪201904)]
# Create new dataframe with the totSales of control store set to 95th percentile
pastSales_Controls95 = pastSales[pastSales['Store_type'] == 'Control'].copy()
pastSales_Controls95['totSales'] = pastSales_Controls95['totSales'] * (1 +␣
  ↪stdDev * 2)
pastSales_Controls95['Store_type'] = 'Control 95th % confidence interval'

# Create new dataframe with the totSales of control store set to 5th percentile
pastSales_Controls5 = pastSales[pastSales['Store_type'] == 'Control'].copy()
pastSales_Controls5['totSales'] = pastSales_Controls5['totSales'] * (1 - stdDev␣
  ↪* 2)
pastSales_Controls5['Store_type'] = 'Control 5th % confidence interval'

# Concat the 3 new dataframes together
trialAssessment = pd.concat([pastSales, pastSales_Controls95,␣
  ↪pastSales_Controls5])
trialAssessment
```

```
[ ]:       STORE_NBR   MONTH     totSales  nCustomers  nTxnPerCust  nChipsPerTxn  \
     984          86  201902   913.200000         107     1.299065      1.992806
     985          86  201903  1026.800000         115     1.234783      2.000000
     986          86  201904   848.200000         105     1.209524      2.000000
     1800        155  201902   891.200000          95     1.336842      2.000000
     1801        155  201903   804.400000          94     1.276596      2.000000
     1802        155  201904   844.600000          99     1.222222      2.000000
     1800        155  201902   958.370328          95     1.336842      2.000000
     1801        155  201903   865.028156          94     1.276596      2.000000
     1802        155  201904   908.258056          99     1.222222      2.000000
     1800        155  201902   824.029672          95     1.336842      2.000000
     1801        155  201903   743.771844          94     1.276596      2.000000
     1802        155  201904   780.941944          99     1.222222      2.000000

           avgPricePerUnit                            Store_type TransactionMonth
     984          3.296751                                 Trial       2019-02-01
     985          3.615493                                 Trial       2019-03-01
     986          3.339370                                 Trial       2019-04-01
     1800         3.508661                               Control       2019-02-01
     1801         3.351667                               Control       2019-03-01
```

```
1802         3.490083                             Control       2019-04-01
1800         3.508661  Control 95th % confidence interval       2019-02-01
1801         3.351667  Control 95th % confidence interval       2019-03-01
1802         3.490083  Control 95th % confidence interval       2019-04-01
1800         3.508661   Control 5th % confidence interval       2019-02-01
1801         3.351667   Control 5th % confidence interval       2019-03-01
1802         3.490083   Control 5th % confidence interval       2019-04-01
```

[ ]:
```
bar = trialAssessment[(trialAssessment['Store_type'] == 'Control') |␣
 ↪(trialAssessment['Store_type'] == 'Trial')]
line = trialAssessment[~((trialAssessment['Store_type'] == 'Control') |␣
 ↪(trialAssessment['Store_type'] == 'Trial'))]

fig, ax = plt.subplots(figsize=(10,10))

sns.barplot(data=bar, x='TransactionMonth', y='totSales', hue='Store_type',␣
 ↪ax=ax)
sns.pointplot(data=line, x='TransactionMonth', y='totSales', hue='Store_type',␣
 ↪ax=ax, palette='dark')
plt.xlabel('Transaction Month')
plt.ylabel('Total Sales')
plt.legend(title='Store type')
plt.title('Total sales by month')
```

[ ]:
```
Text(0.5, 1.0, 'Total sales by month')
```



The results of the sales comparison show that, in terms of sales, the trial in store 86 is not significantly different to its control store in the trial period as the trial store performance lies inside the 5% to 95% confidence interval of the control store in two of the three trial months.

Let us now look at this assessment for the number of customers as well. We will be repeating the process from above and only displaying the outputs relevant to our analysis

[ ]:
```
# Calculate scaling factor
scalingFactor = preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 86) &
 ↪(preTrialMeasures['MONTH'] < 201902)]['nCustomers'].sum() /
 ↪preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 155) &
 ↪(preTrialMeasures['MONTH'] < 201902)]['nCustomers'].sum()

# Apply the scaling factor
```

```
scaledControlCustomers = measureOverTime[measureOverTime['STORE_NBR'] == 155].
 ↪copy()
scaledControlCustomers['controlCustomers'] =␣
 ↪scaledControlCustomers['nCustomers'] * scalingFactor
scaledControlCustomers = scaledControlCustomers[['MONTH', 'STORE_NBR',␣
 ↪'controlCustomers']]

# Calculate the percentage difference between the trial and scaled control␣
 ↪values
percentagediff = pd.merge(scaledControlCustomers,␣
 ↪measureOverTime[measureOverTime['STORE_NBR']==86][['MONTH', 'STORE_NBR',␣
 ↪'nCustomers']], how='left', on='MONTH')
percentagediff['percentageDiff'] = (percentagediff['nCustomers'] -␣
 ↪percentagediff['controlCustomers'])/percentagediff['controlCustomers']

# Calculate the standard deviation
stdDev = percentagediff[percentagediff['MONTH'] < 201902]['percentageDiff'].
 ↪std()
```

- Calculate the t-values of the customer amounts

[ ]:
```
percentagediff['tValue'] = (percentagediff[(percentagediff['MONTH'] >= 201902)␣
 ↪& (percentagediff['MONTH'] <= 201904)]['percentageDiff'] -␣
 ↪percentagediff['percentageDiff'].mean()) / stdDev
trialTable = percentagediff[(percentagediff['MONTH'] >= 201902) &␣
 ↪(percentagediff['MONTH'] <= 201904)]
trialTable
```

[ ]:
```
    MONTH  STORE_NBR_x  controlCustomers  STORE_NBR_y  nCustomers  \
7  201902          155              95.0           86         107
8  201903          155              94.0           86         115
9  201904          155              99.0           86         105

   percentageDiff    tValue
7        0.126316  4.744258
8        0.223404  9.811722
9        0.060606  1.314584
```

- Find the 95th percentile of the t distribution with the appropriate degree of freedom

[ ]:
```
from scipy.stats import t
# Set degrees of freedom
degreesOfFreedom = 7
# Calculate percentile
p = t.ppf(0.95, df=degreesOfFreedom)
print(f'The 95th percentile of the t-distribution is {p}')
```

```
The 95th percentile of the t-distribution is 1.894578605061305
```

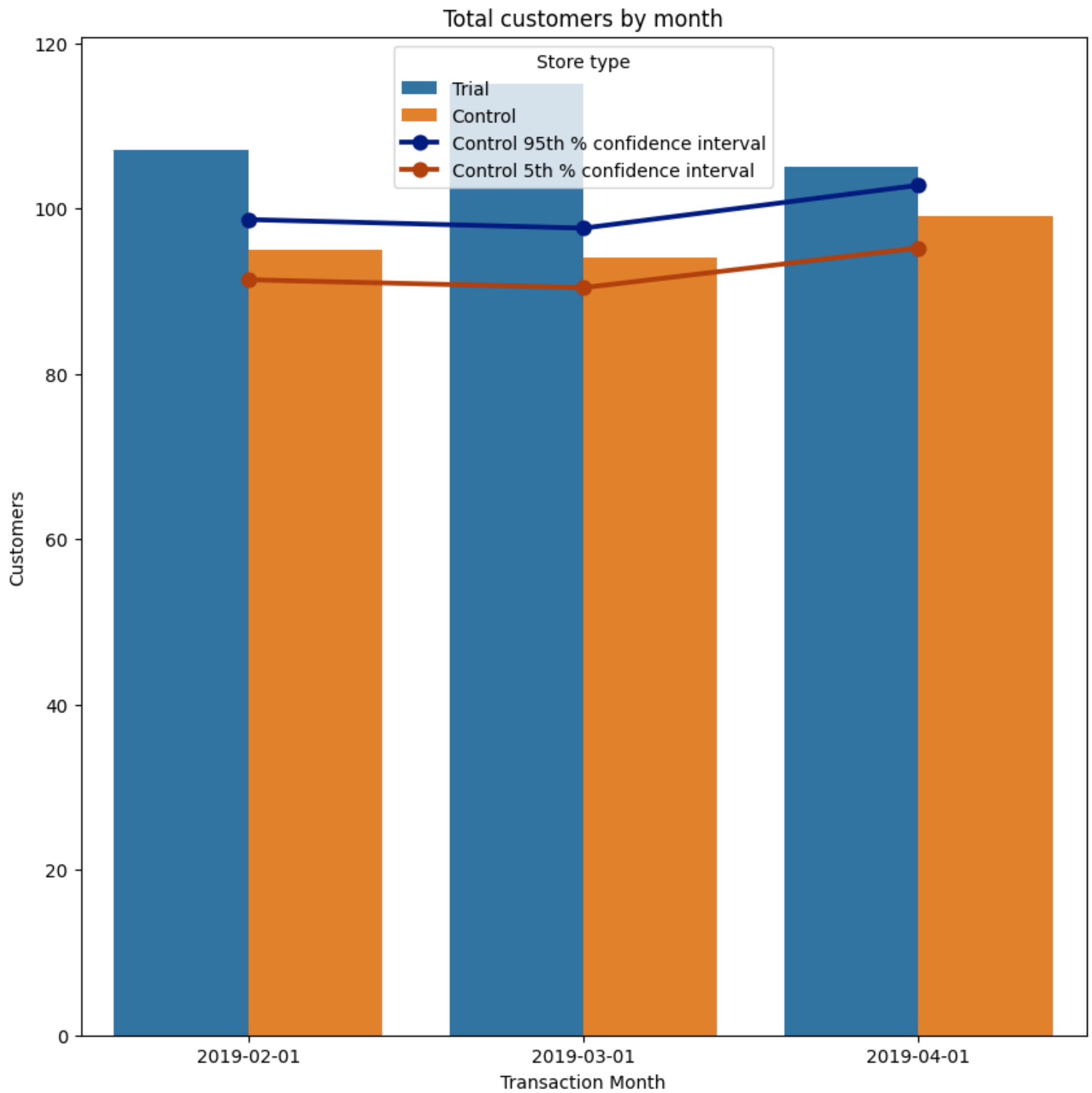
[ ]:
```
# Filter the measureOverTime dataframe for only the control and trial stores
pastCustomers = measureOverTime[(measureOverTime['STORE_NBR']==86) |␣
↪(measureOverTime['STORE_NBR']==155)].copy()
pastCustomers['Store_type'] = pastCustomers.apply(
                                                lambda row: 'Trial' if␣
↪row['STORE_NBR'] == 86
                                                else 'Control',
                                                axis=1
                                            )
pastCustomers['TransactionMonth'] = pd.to_datetime(pastCustomers['MONTH'],␣
↪format='%Y%m')
pastCustomers = pastCustomers[(pastCustomers['MONTH'] >= 201902) &␣
↪(pastCustomers['MONTH'] <= 201904)]

# Create new dataframe with the nCustomers of control store set to 95th␣
↪percentile
pastCustomers_Controls95 = pastCustomers[pastCustomers['Store_type'] ==␣
↪'Control'].copy()
pastCustomers_Controls95['nCustomers'] = pastCustomers_Controls95['nCustomers']␣
↪* (1 + stdDev * 2)
pastCustomers_Controls95['Store_type'] = 'Control 95th % confidence interval'

# Create new dataframe with the nCustomers of control store set to 5th␣
↪percentile
pastCustomers_Controls5 = pastCustomers[pastCustomers['Store_type'] ==␣
↪'Control'].copy()
pastCustomers_Controls5['nCustomers'] = pastCustomers_Controls5['nCustomers'] *␣
↪(1 - stdDev * 2)
pastCustomers_Controls5['Store_type'] = 'Control 5th % confidence interval'

# Concat the 3 new dataframes together
trialAssessment = pd.concat([pastCustomers, pastCustomers_Controls95,␣
↪pastCustomers_Controls5])
trialAssessment
```

[ ]:
```
      STORE_NBR   MONTH  totSales  nCustomers  nTxnPerCust  nChipsPerTxn  \
984          86  201902     913.2  107.000000     1.299065      1.992806
985          86  201903    1026.8  115.000000     1.234783      2.000000
986          86  201904     848.2  105.000000     1.209524      2.000000
1800        155  201902     891.2   95.000000     1.336842      2.000000
1801        155  201903     804.4   94.000000     1.276596      2.000000
1802        155  201904     844.6   99.000000     1.222222      2.000000
1800        155  201902     891.2   98.640244     1.336842      2.000000
1801        155  201903     804.4   97.601926     1.276596      2.000000
1802        155  201904     844.6  102.793518     1.222222      2.000000
1800        155  201902     891.2   91.359756     1.336842      2.000000
```

```
1801         155  201903     804.4   90.398074     1.276596      2.000000
1802         155  201904     844.6   95.206482     1.222222      2.000000

      avgPricePerUnit                            Store_type TransactionMonth
984          3.296751                                 Trial       2019-02-01
985          3.615493                                 Trial       2019-03-01
986          3.339370                                 Trial       2019-04-01
1800         3.508661                               Control       2019-02-01
1801         3.351667                               Control       2019-03-01
1802         3.490083                               Control       2019-04-01
1800         3.508661  Control 95th % confidence interval       2019-02-01
1801         3.351667  Control 95th % confidence interval       2019-03-01
1802         3.490083  Control 95th % confidence interval       2019-04-01
1800         3.508661   Control 5th % confidence interval       2019-02-01
1801         3.351667   Control 5th % confidence interval       2019-03-01
1802         3.490083   Control 5th % confidence interval       2019-04-01
```

[ ]:
```
bar = trialAssessment[(trialAssessment['Store_type'] == 'Control') |
 ↪(trialAssessment['Store_type'] == 'Trial')]
line = trialAssessment[~((trialAssessment['Store_type'] == 'Control') |
 ↪(trialAssessment['Store_type'] == 'Trial'))]

fig, ax = plt.subplots(figsize=(10,10))

sns.barplot(data=bar, x='TransactionMonth', y='nCustomers', hue='Store_type')
sns.pointplot(data=line, x='TransactionMonth', y='nCustomers',
 ↪hue='Store_type', palette='dark')
plt.xlabel('Transaction Month')
plt.ylabel('Customers')
plt.legend(title='Store type')
plt.title('Total customers by month')
```

[ ]:
```
Text(0.5, 1.0, 'Total customers by month')
```



It looks like the number of customers is significantly higher in all of the three months. 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, sales were not significantly higher. 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.

0.2.3 Trial Store 88 analysis

- Calculate the correlation scores for each store with trial store 88 for drivers total sales and customers.

[ ]:
```
# Sales correlation
corr_nSales = calculateCorrelation('totSales', 88)
```

```
corr_nSales
```

[ ]:
```
     CONTROL_STORE  TRIAL_STORE  CORRELATION_SCORE
0                1           88           0.906818
1                2           88           0.466037
2                3           88           0.246076
3                4           88           0.127217
4                5           88           0.595165
..             …          …                …
252            268           88           0.489286
253            269           88           0.413711
254            270           88           0.138364
255            271           88           0.448481
256            272           88           0.113614

[257 rows x 3 columns]
```

[ ]:
```
# Customers correlation
corr_nCustomers = calculateCorrelation('nCustomers', 88)
corr_nCustomers
```

[ ]:
```
     CONTROL_STORE  TRIAL_STORE  CORRELATION_SCORE
0                1           88           0.652667
1                2           88           0.273811
2                3           88           0.761442
3                4           88           0.319249
4                5           88           0.487340
..             …          …                …
252            268           88           0.836336
253            269           88           0.362610
254            270           88           0.448484
255            271           88           0.490585
256            272           88           0.513454

[257 rows x 3 columns]
```

- Next calculate and create tables for the magnitude distance for the drivers between store 86 and the other stores

[ ]:
```
magnitude_nSales = minMaxDist(calculateMagnitudeDistance('totSales', 88))
magnitude_nSales
```

[ ]:
```
     CONTROL_STORE  TRIAL_STORE  mag_measure
0                1           88     0.143453
1                2           88     0.116355
2                3           88     0.806064
3                4           88     0.901383
4                5           88     0.612614
```

```
..            …          …         …
252         268         88  0.161613
253         269         88  0.712728
254         270         88  0.717650
255         271         88  0.615957
256         272         88  0.291095

[257 rows x 3 columns]
```

[ ]:
```python
magnitude_nCustomers = minMaxDist(calculateMagnitudeDistance('nCustomers', 88))
magnitude_nCustomers
```

[ ]:
```
     CONTROL_STORE  TRIAL_STORE  mag_measure
0                1           88     0.353668
1                2           88     0.302289
2                3           88     0.849307
3                4           88     0.930930
4                5           88     0.742127
..             …          …         …
252            268           88     0.337873
253            269           88     0.852599
254            270           88     0.839071
255            271           88     0.743121
256            272           88     0.336616

[257 rows x 3 columns]
```

- The seperate tables for correlation and magnitude distance can now be merged to calculate a final score for each store

[ ]:
```python
scoreNSales = merge_calcs(['totSales'], 88)
```

[ ]:
```python
scoreNCustomers = merge_calcs('nCustomers', 88)
scoreNCustomers
```

[ ]:
```
     CONTROL_STORE  TRIAL_STORE  CORRELATION_SCORE  mag_measure  Merged_Score
0                1           88           0.652667     0.353668      0.503167
1                2           88           0.273811     0.302289      0.288050
2                3           88           0.761442     0.849307      0.805374
3                4           88           0.319249     0.930930      0.625089
4                5           88           0.487340     0.742127      0.614733
..             …          …                …          …           …
252            268           88           0.836336     0.337873      0.587105
253            269           88           0.362610     0.852599      0.607604
254            270           88           0.448484     0.839071      0.643778
255            271           88           0.490585     0.743121      0.616853
256            272           88           0.513454     0.336616      0.425035
```

```
[257 rows x 5 columns]
```

```
[ ]: # Merge score tables to calculate final score
scoreControl = scoreNSales.merge(scoreNCustomers, on= ['TRIAL_STORE',␣
 ↪'CONTROL_STORE'])
scoreControl['Final_Score'] = 0.5 * scoreControl['Merged_Score_x'] + 0.5 *␣
 ↪scoreControl['Merged_Score_y']
scoreControl
```

```
[ ]:      CONTROL_STORE  TRIAL_STORE  CORRELATION_SCORE_x  mag_measure_x  \
0                1           88             0.906818       0.143453
1                2           88             0.466037       0.116355
2                3           88             0.246076       0.806064
3                4           88             0.127217       0.901383
4                5           88             0.595165       0.612614
..             …          …                  …             …
252            268           88             0.489286       0.161613
253            269           88             0.413711       0.712728
254            270           88             0.138364       0.717650
255            271           88             0.448481       0.615957
256            272           88             0.113614       0.291095

     Merged_Score_x  CORRELATION_SCORE_y  mag_measure_y  Merged_Score_y  \
0          0.525135             0.652667       0.353668        0.503167
1          0.291196             0.273811       0.302289        0.288050
2          0.526070             0.761442       0.849307        0.805374
3          0.514300             0.319249       0.930930        0.625089
4          0.603890             0.487340       0.742127        0.614733
..              …                  …             …              …
252        0.325449             0.836336       0.337873        0.587105
253        0.563219             0.362610       0.852599        0.607604
254        0.428007             0.448484       0.839071        0.643778
255        0.532219             0.490585       0.743121        0.616853
256        0.202354             0.513454       0.336616        0.425035

     Final_Score
0       0.514151
1       0.289623
2       0.665722
3       0.569695
4       0.609312
..           …
252     0.456277
253     0.585412
254     0.535892
255     0.574536
256     0.313695
```

```
[257 rows x 9 columns]
```

```
[ ]: # Sort score table to find the closest matching store
scoreControl.sort_values('Final_Score', ascending=False).head()
```

```
[ ]:      CONTROL_STORE  TRIAL_STORE  CORRELATION_SCORE_x  mag_measure_x  \
222            237           88             0.654240       0.960010
167            178           88             0.865928       0.698766
189            201           88             0.746367       0.876633
191            203           88             0.754001       0.954734
112            123           88             0.699881       0.859722

     Merged_Score_x  CORRELATION_SCORE_y  mag_measure_y  Merged_Score_y  \
222        0.807125             0.973663       0.994284        0.983974
167        0.782347             0.969733       0.826829        0.898281
189        0.811500             0.755651       0.926770        0.841211
191        0.854367             0.642531       0.949543        0.796037
112        0.779801             0.813963       0.900552        0.857257

     Final_Score
222     0.895549
167     0.840314
189     0.826356
191     0.825202
112     0.818529
```

```
[ ]: scoreControl[scoreControl['CONTROL_STORE']==237]
```

```
[ ]:      CONTROL_STORE  TRIAL_STORE  CORRELATION_SCORE_x  mag_measure_x  \
222            237           88              0.65424        0.96001

     Merged_Score_x  CORRELATION_SCORE_y  mag_measure_y  Merged_Score_y  \
222        0.807125             0.973663       0.994284        0.983974

     Final_Score
222     0.895549
```

The store with the highest final score, and therefore the closest to the selected trial store, is Store 237. Now that we have found a control store, let's visually check if the drivers are indeed similar in the period before the trial.

- We will first filter the driver data for the stores

```
[ ]: # Filter the measureOverTime dataframe for only the control and trial stores
pastSales = measureOverTime[(measureOverTime['STORE_NBR']==88) |␣
 ↪(measureOverTime['STORE_NBR']==237)].copy()
pastSales['Store_type'] = pastSales.apply(
```

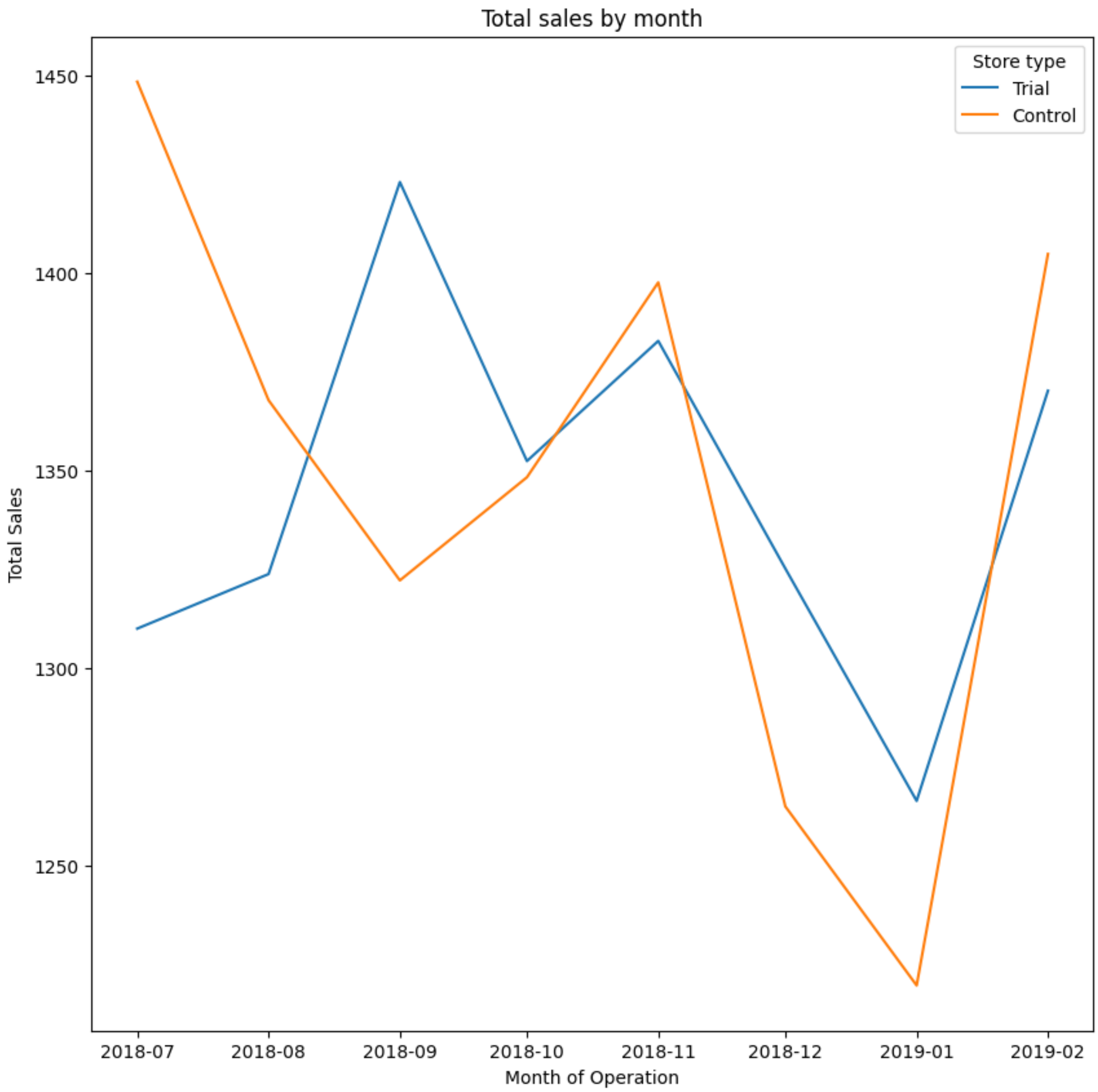
```
                                                            lambda row: 'Trial' if␣
↪row['STORE_NBR'] == 88
                                                            else 'Control',
                                                            axis=1
                                                        )
pastSales['TransactionMonth'] = pd.to_datetime(pastSales['MONTH'],␣
↪format='%Y%m')
pastSales = pastSales[pastSales['MONTH'] < 201903]
pastSales.head()
```

```
[ ]:       STORE_NBR   MONTH  totSales  nCustomers  nTxnPerCust  nChipsPerTxn  \
1001          88  201807    1310.0         129     1.186047       2.00000
1002          88  201808    1323.8         131     1.221374       1.89375
1003          88  201809    1423.0         124     1.282258       2.00000
1004          88  201810    1352.4         123     1.284553       2.00000
1005          88  201811    1382.8         130     1.207692       2.00000

      avgPricePerUnit Store_type TransactionMonth
1001         4.281046      Trial       2018-07-01
1002         4.368977      Trial       2018-08-01
1003         4.474843      Trial       2018-09-01
1004         4.279747      Trial       2018-10-01
1005         4.403822      Trial       2018-11-01
```

- Next we will plot the total sales for both stores to visually compare them

```
[ ]: # Plot graph
plt.figure(figsize=(10,10))
sns.lineplot(pastSales, x='TransactionMonth', y='totSales', hue='Store_type')
plt.xlabel('Month of Operation')
plt.ylabel('Total Sales')
plt.title('Total sales by month')
plt.legend(title= 'Store type')
```

```
[ ]: <matplotlib.legend.Legend at 0x7f92186eb9d0>
```



- We will do the same for customers

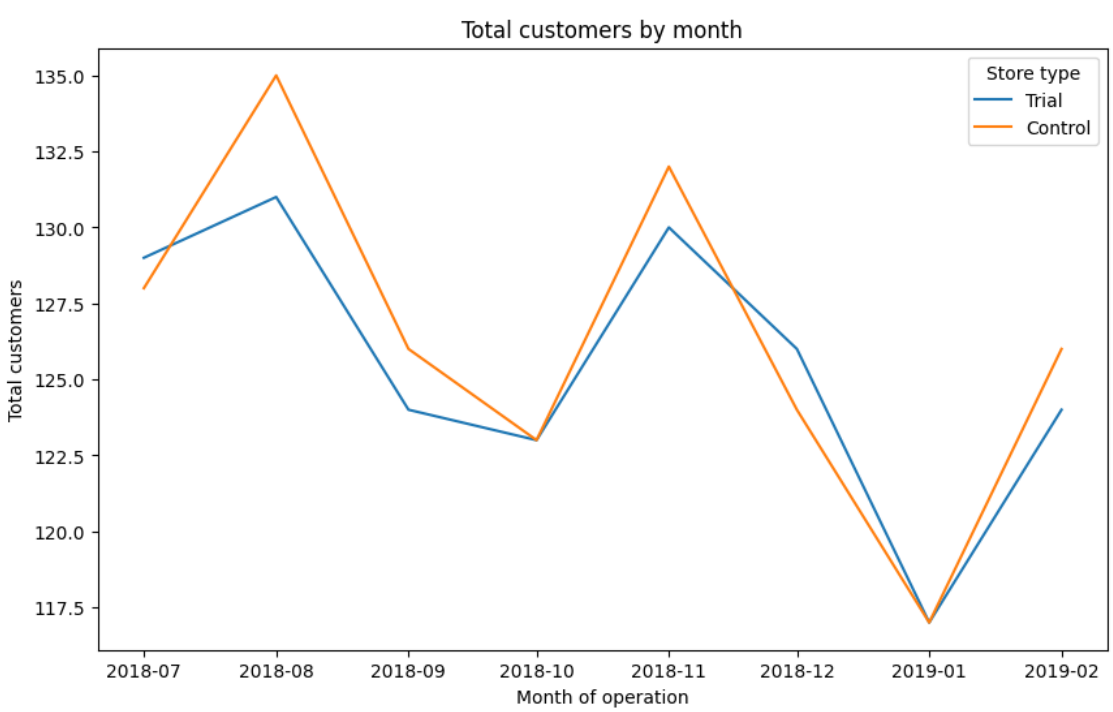
[ ]:
```
pastCustomers = measureOverTime[(measureOverTime['STORE_NBR']==88) |␣
↪(measureOverTime['STORE_NBR']==237)].copy()
pastCustomers['Store_type'] = pastCustomers.apply(
                                              lambda row: 'Trial' if␣
↪row['STORE_NBR'] == 88
                                              else 'Control',
                                              axis=1
                                             )
pastCustomers['TransactionMonth'] = pd.to_datetime(pastCustomers['MONTH'],␣
↪format='%Y%m')
pastCustomers = pastCustomers[pastCustomers['MONTH'] < 201903]
```

```
pastCustomers.head()
```

[ ]:
```
      STORE_NBR   MONTH  totSales  nCustomers  nTxnPerCust  nChipsPerTxn  \
1001         88  201807    1310.0         129     1.186047       2.00000
1002         88  201808    1323.8         131     1.221374       1.89375
1003         88  201809    1423.0         124     1.282258       2.00000
1004         88  201810    1352.4         123     1.284553       2.00000
1005         88  201811    1382.8         130     1.207692       2.00000

      avgPricePerUnit Store_type TransactionMonth
1001         4.281046      Trial       2018-07-01
1002         4.368977      Trial       2018-08-01
1003         4.474843      Trial       2018-09-01
1004         4.279747      Trial       2018-10-01
1005         4.403822      Trial       2018-11-01
```

[ ]:
```
# Plot the data using Matplotlib
plt.figure(figsize=(10, 6))
sns.lineplot(pastCustomers, x='TransactionMonth', y='nCustomers',␣
 ↪hue='Store_type')
plt.xlabel('Month of operation')
plt.ylabel('Total customers')
plt.title('Total customers by month')
plt.legend(title='Store type')
```

[ ]:
```
<matplotlib.legend.Legend at 0x7f9218554790>
```



Next we will compare the results of the trial period for the trial and control stores

- Scale pre-trial control sales to match pre-trial trial store sales

```
[ ]: # Calculate scaling factor
scalingFactor = preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 88) &␣
 ↪(preTrialMeasures['MONTH'] < 201902)]['totSales'].sum() /␣
 ↪preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 237) &␣
 ↪(preTrialMeasures['MONTH'] < 201902)]['totSales'].sum()

# Apply the scaling factor
scaledControlSales = measureOverTime[measureOverTime['STORE_NBR'] == 237].copy()
scaledControlSales['controlSales'] = scaledControlSales['totSales'] *␣
 ↪scalingFactor
scaledControlSales = scaledControlSales[['MONTH', 'STORE_NBR', 'controlSales']]
scaledControlSales
```

[ ]:

	MONTH	STORE_NBR	controlSales
2747	201807	237	1450.657086
2748	201808	237	1369.931485
2749	201809	237	1324.260425
2750	201810	237	1350.401097
2751	201811	237	1399.777923
2752	201812	237	1266.971288
2753	201901	237	1221.600696
2754	201902	237	1406.989143
2755	201903	237	1210.082775
2756	201904	237	1206.477165
2757	201905	237	1201.168906
2758	201906	237	1155.397690

- Calculate the percentage difference between scaled control sales and trial sales

```
[ ]: percentagediff = pd.merge(scaledControlSales,␣
 ↪measureOverTime[measureOverTime['STORE_NBR']==88][['MONTH', 'STORE_NBR',␣
 ↪'totSales']], how='left', on='MONTH')
percentagediff['percentageDiff'] = (percentagediff['totSales'] -␣
 ↪percentagediff['controlSales'])/percentagediff['controlSales']
percentagediff
```

[ ]:

	MONTH	STORE_NBR_x	controlSales	STORE_NBR_y	totSales	percentageDiff
0	201807	237	1450.657086	88	1310.00	-0.096961
1	201808	237	1369.931485	88	1323.80	-0.033674
2	201809	237	1324.260425	88	1423.00	0.074562
3	201810	237	1350.401097	88	1352.40	0.001480
4	201811	237	1399.777923	88	1382.80	-0.012129

```
5   201812        237   1266.971288        88   1325.20        0.045959
6   201901        237   1221.600696        88   1266.40        0.036673
7   201902        237   1406.989143        88   1370.20       -0.026147
8   201903        237   1210.082775        88   1477.20        0.220743
9   201904        237   1206.477165        88   1439.40        0.193060
10  201905        237   1201.168906        88   1308.25        0.089147
11  201906        237   1155.397690        88   1354.60        0.172410
```

- Calculate the standard deviation for the percentage difference between sales over the period

[ ]:
```
stdDev = percentagediff[percentagediff['MONTH'] < 201902]['percentageDiff'].
 ↪std()
stdDev
```

[ ]:
```
0.05724965451900225
```

- Calculate the t-values of the trial months

[ ]:
```
percentagediff['tValue'] = (percentagediff[(percentagediff['MONTH'] >= 201902)␣
 ↪& (percentagediff['MONTH'] <= 201904)]['percentageDiff'] -␣
 ↪percentagediff['percentageDiff'].mean()) / stdDev
trialTable = percentagediff[(percentagediff['MONTH'] >= 201902) &␣
 ↪(percentagediff['MONTH'] <= 201904)]
trialTable
```

[ ]:
```
     MONTH  STORE_NBR_x  controlSales  STORE_NBR_y  totSales  percentageDiff  \
7   201902          237   1406.989143           88    1370.2       -0.026147
8   201903          237   1210.082775           88    1477.2        0.220743
9   201904          237   1206.477165           88    1439.4        0.193060

      tValue
7 -1.424888
8  2.887633
9  2.404091
```

- Find the 95th percentile of the t distribution with the appropriate degree of freedom

[ ]:
```
from scipy.stats import t
# Set degrees of freedom
degreesOfFreedom = 7
# Calculate percentile
p = t.ppf(0.95, df=degreesOfFreedom)
print(f'The 95th percentile of the t-distribution is {p}')
```

```
The 95th percentile of the t-distribution is 1.894578605061305
```

Next we will compare the results of the trial period for the trial and control stores

- Scale pre-trial control sales to match pre-trial trial store sales

[ ]:
```
# Calculate scaling factor
scalingFactor = preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 88) &
 ↪(preTrialMeasures['MONTH'] < 201902)]['totSales'].sum() /
 ↪preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 237) &
 ↪(preTrialMeasures['MONTH'] < 201902)]['totSales'].sum()

# Apply the scaling factor
scaledControlSales = measureOverTime[measureOverTime['STORE_NBR'] == 237].copy()
scaledControlSales['controlSales'] = scaledControlSales['totSales'] *
 ↪scalingFactor
scaledControlSales = scaledControlSales[['MONTH', 'STORE_NBR', 'controlSales']]
scaledControlSales
```

[ ]:

	MONTH	STORE_NBR	controlSales
2747	201807	237	1450.657086
2748	201808	237	1369.931485
2749	201809	237	1324.260425
2750	201810	237	1350.401097
2751	201811	237	1399.777923
2752	201812	237	1266.971288
2753	201901	237	1221.600696
2754	201902	237	1406.989143
2755	201903	237	1210.082775
2756	201904	237	1206.477165
2757	201905	237	1201.168906
2758	201906	237	1155.397690

- Calculate the percentage difference between scaled control sales and trial sales

[ ]:
```
percentagediff = pd.merge(scaledControlSales,
 ↪measureOverTime[measureOverTime['STORE_NBR']==88][['MONTH', 'STORE_NBR',
 ↪'totSales']], how='left', on='MONTH')
percentagediff['percentageDiff'] = (percentagediff['totSales'] -
 ↪percentagediff['controlSales'])/percentagediff['controlSales']
percentagediff
```

[ ]:

	MONTH	STORE_NBR_x	controlSales	STORE_NBR_y	totSales	percentageDiff
0	201807	237	1450.657086	88	1310.00	-0.096961
1	201808	237	1369.931485	88	1323.80	-0.033674
2	201809	237	1324.260425	88	1423.00	0.074562
3	201810	237	1350.401097	88	1352.40	0.001480
4	201811	237	1399.777923	88	1382.80	-0.012129
5	201812	237	1266.971288	88	1325.20	0.045959
6	201901	237	1221.600696	88	1266.40	0.036673
7	201902	237	1406.989143	88	1370.20	-0.026147
8	201903	237	1210.082775	88	1477.20	0.220743
9	201904	237	1206.477165	88	1439.40	0.193060

```
10  201905           237   1201.168906          88   1308.25         0.089147
11  201906           237   1155.397690          88   1354.60         0.172410
```

- Calculate the standard deviation for the percentage difference between sales over the period

```
[ ]: stdDev = percentagediff[percentagediff['MONTH'] < 201902]['percentageDiff'].
     ↪std()
     stdDev
```

```
[ ]: 0.05724965451900225
```

- Calculate the t-values of the trial months

```
[ ]: percentagediff['tValue'] = (percentagediff[(percentagediff['MONTH'] >= 201902)␣
     ↪& (percentagediff['MONTH'] <= 201904)]['percentageDiff'] -␣
     ↪percentagediff['percentageDiff'].mean()) / stdDev
     trialTable = percentagediff[(percentagediff['MONTH'] >= 201902) &␣
     ↪(percentagediff['MONTH'] <= 201904)]
     trialTable
```

```
[ ]:     MONTH  STORE_NBR_x  controlSales  STORE_NBR_y  totSales  percentageDiff  \
     7  201902          237   1406.989143           88    1370.2       -0.026147
     8  201903          237   1210.082775           88    1477.2        0.220743
     9  201904          237   1206.477165           88    1439.4        0.193060

          tValue
     7 -1.424888
     8  2.887633
     9  2.404091
```

- Find the 95th percentile of the t distribution with the appropriate degree of freedom

```
[ ]: from scipy.stats import t
     # Set degrees of freedom
     degreesOfFreedom = 7
     # Calculate percentile
     p = t.ppf(0.95, df=degreesOfFreedom)
     print(f'The 95th percentile of the t-distribution is {p}')
```

```
The 95th percentile of the t-distribution is 1.894578605061305
```

Let's visualize this by plotting the sales and the confidence intervals of the stores for the trial period.

- Filter data for the 2 stores total sales, and the 95th and 5th percentiles of the control store sales

```
[ ]: # Filter the measureOverTime dataframe for only the control and trial stores
     pastSales = measureOverTime[(measureOverTime['STORE_NBR']==88) |␣
     ↪(measureOverTime['STORE_NBR']==237)].copy()
```

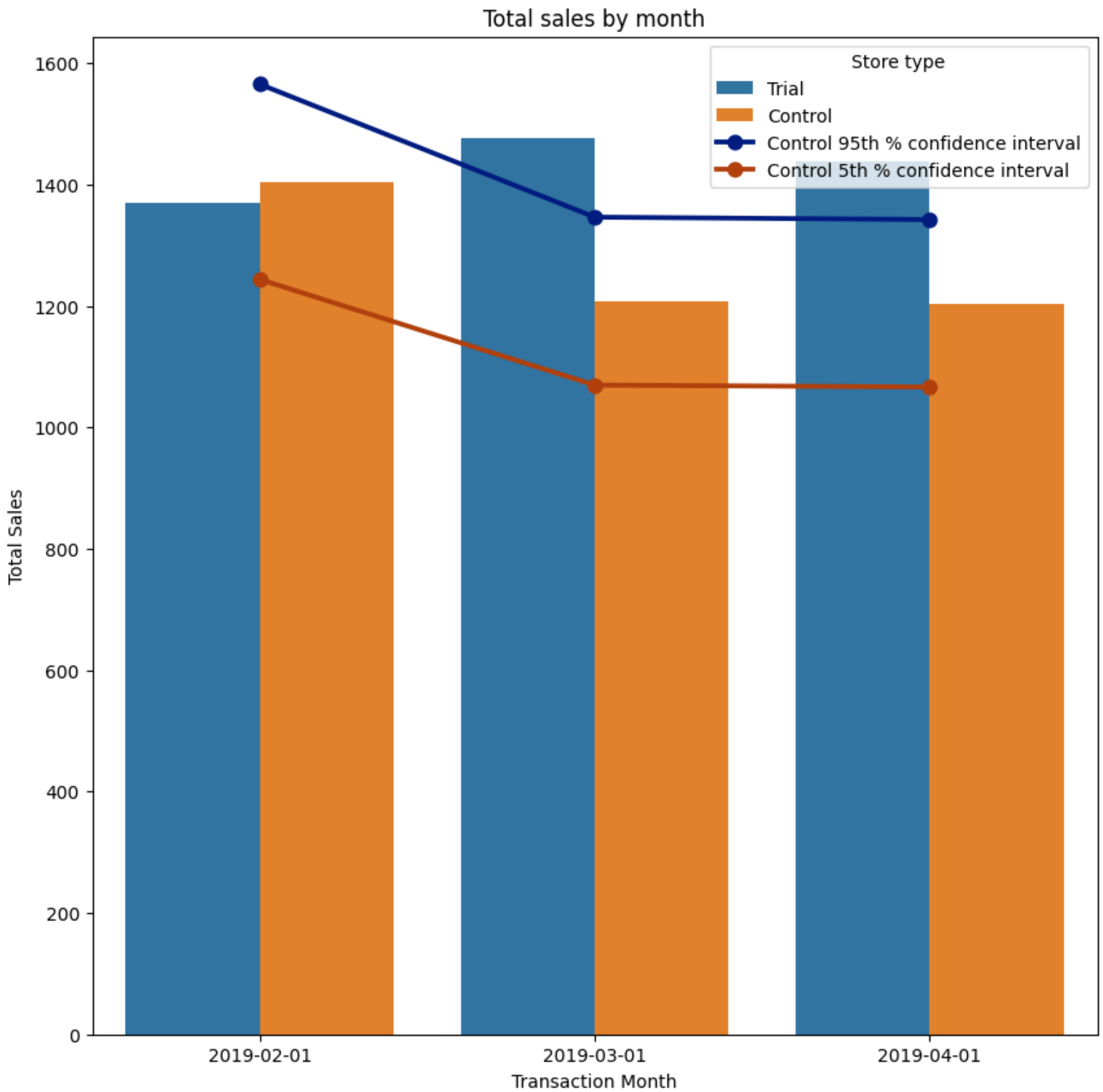
```
pastSales['Store_type'] = pastSales.apply(
                                                    lambda row: 'Trial' if␣
↪row['STORE_NBR'] == 88
                                                    else 'Control',
                                                    axis=1
                                                )
pastSales['TransactionMonth'] = pd.to_datetime(pastSales['MONTH'],␣
↪format='%Y%m')
pastSales = pastSales[(pastSales['MONTH'] >= 201902) & (pastSales['MONTH'] <=␣
↪201904)]
# Create new dataframe with the totSales of control store set to 95th percentile
pastSales_Controls95 = pastSales[pastSales['Store_type'] == 'Control'].copy()
pastSales_Controls95['totSales'] = pastSales_Controls95['totSales'] * (1 +␣
↪stdDev * 2)
pastSales_Controls95['Store_type'] = 'Control 95th % confidence interval'

# Create new dataframe with the totSales of control store set to 5th percentile
pastSales_Controls5 = pastSales[pastSales['Store_type'] == 'Control'].copy()
pastSales_Controls5['totSales'] = pastSales_Controls5['totSales'] * (1 - stdDev␣
↪* 2)
pastSales_Controls5['Store_type'] = 'Control 5th % confidence interval'

# Concat the 3 new dataframes together
trialAssessment = pd.concat([pastSales, pastSales_Controls95,␣
↪pastSales_Controls5])
trialAssessment
```

[ ]:
```
      STORE_NBR   MONTH     totSales  nCustomers  nTxnPerCust  nChipsPerTxn  \
1008         88  201902  1370.200000         124     1.241935           2.0
1009         88  201903  1477.200000         134     1.268657           2.0
1010         88  201904  1439.400000         128     1.265625           2.0
2754        237  201902  1404.800000         126     1.246032           2.0
2755        237  201903  1208.200000         119     1.151261           2.0
2756        237  201904  1204.600000         120     1.133333           2.0
2754        237  201902  1565.648629         126     1.246032           2.0
2755        237  201903  1346.538065         119     1.151261           2.0
2756        237  201904  1342.525868         120     1.133333           2.0
2754        237  201902  1243.951371         126     1.246032           2.0
2755        237  201903  1069.861935         119     1.151261           2.0
2756        237  201904  1066.674132         120     1.133333           2.0

      avgPricePerUnit                          Store_type TransactionMonth
1008         4.448701                               Trial       2019-02-01
1009         4.344706                               Trial       2019-03-01
1010         4.442593                               Trial       2019-04-01
2754         4.473885                             Control       2019-02-01
2755         4.409489                             Control       2019-03-01
```

```
2756          4.428676                              Control       2019-04-01
2754          4.473885  Control 95th % confidence interval       2019-02-01
2755          4.409489  Control 95th % confidence interval       2019-03-01
2756          4.428676  Control 95th % confidence interval       2019-04-01
2754          4.473885   Control 5th % confidence interval       2019-02-01
2755          4.409489   Control 5th % confidence interval       2019-03-01
2756          4.428676   Control 5th % confidence interval       2019-04-01
```

[ ]:
```
bar = trialAssessment[(trialAssessment['Store_type'] == 'Control') |
    (trialAssessment['Store_type'] == 'Trial')]
line = trialAssessment[~((trialAssessment['Store_type'] == 'Control') |
    (trialAssessment['Store_type'] == 'Trial'))]

fig, ax = plt.subplots(figsize=(10,10))

sns.barplot(data=bar, x='TransactionMonth', y='totSales', hue='Store_type',
    ax=ax)
sns.pointplot(data=line, x='TransactionMonth', y='totSales', hue='Store_type',
    ax=ax, palette='dark')
plt.xlabel('Transaction Month')
plt.ylabel('Total Sales')
plt.legend(title='Store type')
plt.title('Total sales by month')
```

[ ]:
```
Text(0.5, 1.0, 'Total sales by month')
```



The results show that the trial in store 88 is significantly different to its control store in the trial period as the trial store performance lies outside of the 5% to 95% confidence interval of the control store in two of the three trial months.

Let us now look at this assessment for the number of customers as well. We will be repeating the process from above and only displaying the outputs relevant to our analysis

[ ]:
```
# Calculate scaling factor
scalingFactor = preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 86) &␣
↪(preTrialMeasures['MONTH'] < 201902)]['nCustomers'].sum() /␣
↪preTrialMeasures[(preTrialMeasures['STORE_NBR'] == 155) &␣
↪(preTrialMeasures['MONTH'] < 201902)]['nCustomers'].sum()

# Apply the scaling factor
```

```
scaledControlCustomers = measureOverTime[measureOverTime['STORE_NBR'] == 155].
 ↪copy()
scaledControlCustomers['controlCustomers'] =␣
 ↪scaledControlCustomers['nCustomers'] * scalingFactor
scaledControlCustomers = scaledControlCustomers[['MONTH', 'STORE_NBR',␣
 ↪'controlCustomers']]

# Calculate the percentage difference between the trial and scaled control␣
 ↪values
percentagediff = pd.merge(scaledControlCustomers,␣
 ↪measureOverTime[measureOverTime['STORE_NBR']==86][['MONTH', 'STORE_NBR',␣
 ↪'nCustomers']], how='left', on='MONTH')
percentagediff['percentageDiff'] = (percentagediff['nCustomers'] -␣
 ↪percentagediff['controlCustomers'])/percentagediff['controlCustomers']

# Calculate the standard deviation
stdDev = percentagediff[percentagediff['MONTH'] < 201902]['percentageDiff'].
 ↪std()
```

- Calculate the t-values of the customer amounts

[ ]:
```
percentagediff['tValue'] = (percentagediff[(percentagediff['MONTH'] >= 201902)␣
 ↪& (percentagediff['MONTH'] <= 201904)]['percentageDiff'] -␣
 ↪percentagediff['percentageDiff'].mean()) / stdDev
trialTable = percentagediff[(percentagediff['MONTH'] >= 201902) &␣
 ↪(percentagediff['MONTH'] <= 201904)]
trialTable
```

[ ]:
```
    MONTH  STORE_NBR_x  controlCustomers  STORE_NBR_y  nCustomers  \
7  201902          155              95.0           86         107
8  201903          155              94.0           86         115
9  201904          155              99.0           86         105

   percentageDiff    tValue
7        0.126316  4.744258
8        0.223404  9.811722
9        0.060606  1.314584
```

- Find the 95th percentile of the t distribution with the appropriate degree of freedom

[ ]:
```
from scipy.stats import t
# Set degrees of freedom
degreesOfFreedom = 7
# Calculate percentile
p = t.ppf(0.95, df=degreesOfFreedom)
print(f'The 95th percentile of the t-distribution is {p}')
```

```
The 95th percentile of the t-distribution is 1.894578605061305
```

[ ]:
```
# Filter the measureOverTime dataframe for only the control and trial stores
pastCustomers = measureOverTime[(measureOverTime['STORE_NBR']==86) |␣
↪(measureOverTime['STORE_NBR']==155)].copy()
pastCustomers['Store_type'] = pastCustomers.apply(
                                                lambda row: 'Trial' if␣
↪row['STORE_NBR'] == 86
                                                else 'Control',
                                                axis=1
                                            )
pastCustomers['TransactionMonth'] = pd.to_datetime(pastCustomers['MONTH'],␣
↪format='%Y%m')
pastCustomers = pastCustomers[(pastCustomers['MONTH'] >= 201902) &␣
↪(pastCustomers['MONTH'] <= 201904)]

# Create new dataframe with the nCustomers of control store set to 95th␣
↪percentile
pastCustomers_Controls95 = pastCustomers[pastCustomers['Store_type'] ==␣
↪'Control'].copy()
pastCustomers_Controls95['nCustomers'] = pastCustomers_Controls95['nCustomers']␣
↪* (1 + stdDev * 2)
pastCustomers_Controls95['Store_type'] = 'Control 95th % confidence interval'

# Create new dataframe with the nCustomers of control store set to 5th␣
↪percentile
pastCustomers_Controls5 = pastCustomers[pastCustomers['Store_type'] ==␣
↪'Control'].copy()
pastCustomers_Controls5['nCustomers'] = pastCustomers_Controls5['nCustomers'] *␣
↪(1 - stdDev * 2)
pastCustomers_Controls5['Store_type'] = 'Control 5th % confidence interval'

# Concat the 3 new dataframes together
trialAssessment = pd.concat([pastCustomers, pastCustomers_Controls95,␣
↪pastCustomers_Controls5])
trialAssessment
```

[ ]:

	STORE_NBR	MONTH	totSales	nCustomers	nTxnPerCust	nChipsPerTxn	\
984	86	201902	913.2	107.000000	1.299065	1.992806	
985	86	201903	1026.8	115.000000	1.234783	2.000000	
986	86	201904	848.2	105.000000	1.209524	2.000000	
1800	155	201902	891.2	95.000000	1.336842	2.000000	
1801	155	201903	804.4	94.000000	1.276596	2.000000	
1802	155	201904	844.6	99.000000	1.222222	2.000000	
1800	155	201902	891.2	98.640244	1.336842	2.000000	
1801	155	201903	804.4	97.601926	1.276596	2.000000	
1802	155	201904	844.6	102.793518	1.222222	2.000000	
1800	155	201902	891.2	91.359756	1.336842	2.000000	

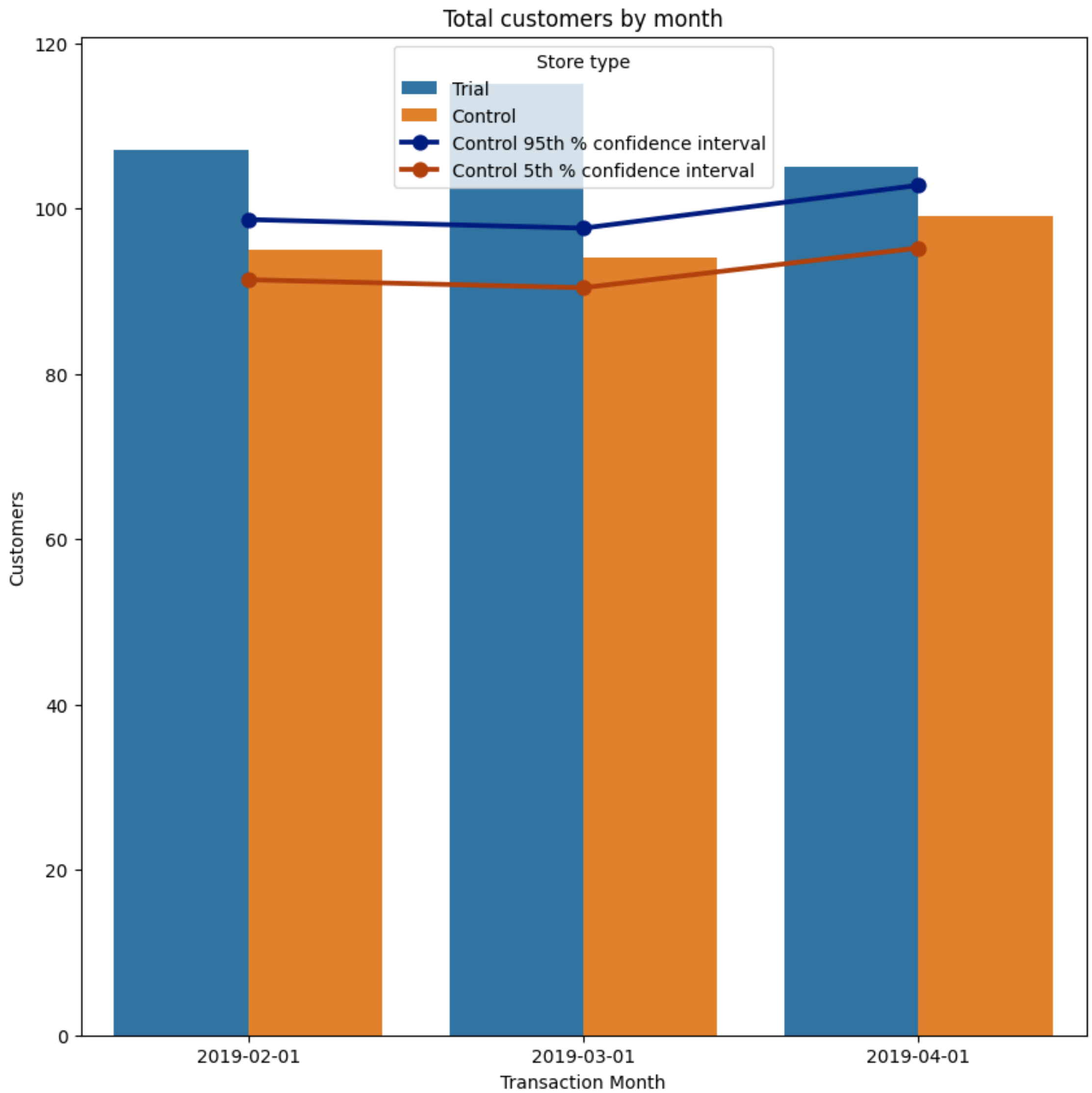
```
1801         155  201903     804.4    90.398074     1.276596      2.000000
1802         155  201904     844.6    95.206482     1.222222      2.000000

      avgPricePerUnit                          Store_type TransactionMonth
984          3.296751                               Trial       2019-02-01
985          3.615493                               Trial       2019-03-01
986          3.339370                               Trial       2019-04-01
1800         3.508661                             Control       2019-02-01
1801         3.351667                             Control       2019-03-01
1802         3.490083                             Control       2019-04-01
1800         3.508661  Control 95th % confidence interval       2019-02-01
1801         3.351667  Control 95th % confidence interval       2019-03-01
1802         3.490083  Control 95th % confidence interval       2019-04-01
1800         3.508661   Control 5th % confidence interval       2019-02-01
1801         3.351667   Control 5th % confidence interval       2019-03-01
1802         3.490083   Control 5th % confidence interval       2019-04-01
```

[ ]:

```
bar = trialAssessment[(trialAssessment['Store_type'] == 'Control') |
 ↪(trialAssessment['Store_type'] == 'Trial')]
line = trialAssessment[~((trialAssessment['Store_type'] == 'Control') |
 ↪(trialAssessment['Store_type'] == 'Trial'))]

fig, ax = plt.subplots(figsize=(10,10))

sns.barplot(data=bar, x='TransactionMonth', y='nCustomers', hue='Store_type')
sns.pointplot(data=line, x='TransactionMonth', y='nCustomers',
 ↪hue='Store_type', palette='dark')
plt.xlabel('Transaction Month')
plt.ylabel('Customers')
plt.legend(title='Store type')
plt.title('Total customers by month')
```

[ ]:

```
Text(0.5, 1.0, 'Total customers by month')
```



Total number of customers in the trial period for the trial store is significantly higher than the control store for two out of three months, which indicates a positive trial effect.