In [1]: import pandas as pd
 import numpy as np
 import matplotlib.pyplot as plt
 import seaborn as sns
 %matplotlib inline
 df= pd.read\_csv(r'C:\Users\Ceejay\Downloads\QVI\_data.csv')
 df.head(12)

### Out[1]:

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY
0	1000	2018- 10-17	1	1	5	Natural Chip Compny SeaSalt175g	2
1	1002	2018- 09-16	1	2	58	Red Rock Deli Chikn&Garlic Aioli 150g	1
2	1003	2019- 03-07	1	3	52	Grain Waves Sour Cream&Chives 210G	1
3	1003	2019- 03-08	1	4	106	Natural ChipCo Hony Soy Chckn175g	1
4	1004	2018- 11-02	1	5	96	WW Original Stacked Chips 160g	1
5	1005	2018- 12-28	1	6	86	Cheetos Puffs 165g	1
6	1007	2018- 12-04	1	7	49	Infuzions SourCream&Herbs Veg Strws 110g	1
7	1007	2018- 12-05	1	8	10	RRD SR Slow Rst Pork Belly 150g	1
8	1009	2018- 11-20	1	9	20	Doritos Cheese Supreme 330g	1
9	1010	2018- 09-09	1	10	51	Doritos Mexicana 170g	2
10	1010	2018- 12-14	1	11	59	Old El Paso Salsa Dip Tomato Med 300g	1
11	1011	2018- 07-29	1	12	84	GrnWves Plus Btroot & Chilli Jam 180g	2
4							•

```
In [2]: | df.info()
```

<class 'pandas.core.frame.DataFrame'> RangeIndex: 264834 entries, 0 to 264833 Data columns (total 12 columns):

#	Column	Non-Null Count	Dtype
0	LYLTY_CARD_NBR	264834 non-null	int64
1	DATE	264834 non-null	object
2	STORE_NBR	264834 non-null	int64
3	TXN_ID	264834 non-null	int64
4	PROD_NBR	264834 non-null	int64
5	PROD_NAME	264834 non-null	object
6	PROD_QTY	264834 non-null	int64
7	TOT_SALES	264834 non-null	float64
8	PACK_SIZE	264834 non-null	int64
9	BRAND	264834 non-null	object
10	LIFESTAGE	264834 non-null	object
11	PREMIUM_CUSTOMER	264834 non-null	object
dtyp	es: float64(1), in	t64(6), object(5)	1

memory usage: 24.2+ MB

```
In [3]: df['DATE']= pd.to_datetime(df.DATE)
```

A column containing the year and the month of the transaction will be created. This would then be used to group the data.

```
In [4]: df['YEARMO']= df.DATE.dt.strftime('%y-%m')
```

In [5]: df.head()

Out[5]:

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	тот
0	1000	2018- 10-17	1	1	5	Natural Chip Compny SeaSalt175g	2	
1	1002	2018- 09-16	1	2	58	Red Rock Deli Chikn&Garlic Aioli 150g	1	
2	1003	2019- 03-07	1	3	52	Grain Waves Sour Cream&Chives 210G	1	
3	1003	2019- 03-08	1	4	106	Natural ChipCo Hony Soy Chckn175g	1	
4	1004	2018- 11-02	1	5	96	WW Original Stacked Chips 160g	1	
4								•

We can find the total sales each month, for each of the stores.

```
In [6]: sales= df.groupby(['STORE_NBR', 'YEARMO'])['TOT_SALES'].sum()
    sales= sales.to_frame()
```

Likewise, we can also find the total number of unique customers that visited each month for each of the stores

```
In [7]: customers= df.groupby(['STORE_NBR', 'YEARMO'])['LYLTY_CARD_NBR'].nunique()
    customers= customers.to_frame()
```

We can also get the number of transactions that occured each month. This will be used to derive the average transaction per customer metric after concatenating the various 'mini datasets'. After that this column will be removed from the new dataset.

```
In [8]: trans_per_cust= df.groupby(['STORE_NBR', 'YEARMO'])['TXN_ID'].nunique()
    trans_per_cust= trans_per_cust.to_frame()
```

```
In [9]: data= pd.concat([sales, customers, trans_per_cust], axis= 1)
    data['TRANSACT_PER_CUST']= data['TXN_ID']/data['LYLTY_CARD_NBR']
    data.drop('TXN_ID', axis= 1, inplace= True)
```

We will now rename the columns for easier understanding of the variables...

```
In [10]: data.columns= ['tot_sales', 'tot_customers', 'txn_per_customer']
```

```
In [11]: data
```

#### Out[11]:

tot\_sales tot\_customers txn\_per\_customer

STORE_NBR	YEARMO			
1	18-07	206.9	49	1.061224
	18-08	176.1	42	1.023810
	18-09	278.8	59	1.050847
	18-10	188.1	44	1.022727
	18-11	192.6	46	1.021739
272	19-02	395.5	45	1.066667
	19-03	442.3	50	1.060000
	19-04	445.1	54	1.018519
	19-05	314.6	34	1.176471
	19-06	312.1	34	1.088235

3169 rows × 3 columns

Now, we remove stores where the monthly records were not recorded....

```
no_record= pd.pivot_table(df, index= 'STORE_NBR', columns= 'YEARMO', values=
In [12]:
In [13]:
            no record
Out[13]:
                                       18-
                                                                            19-
                                                                                    19-
                                                                                           19-
                                                                                                                  19-
                               18-
                                              18-
                                                      18-
                                                                     18-
                                                                                                   19-
                                                                                                          19-
                                                           18-11
                 YEARMO
                               07
                                       80
                                               09
                                                      10
                                                                     12
                                                                             01
                                                                                    02
                                                                                            03
                                                                                                   04
                                                                                                           05
                                                                                                                  06
             STORE_NBR
                         1
                              52.0
                                     43.0
                                             62.0
                                                    45.0
                                                            47.0
                                                                   47.0
                                                                           36.0
                                                                                  55.0
                                                                                          49.0
                                                                                                 43.0
                                                                                                         51.0
                                                                                                                 43.0
                         2
                              41.0
                                     43.0
                                             37.0
                                                    43.0
                                                            40.0
                                                                   38.0
                                                                           45.0
                                                                                  32.0
                                                                                          46.0
                                                                                                 49.0
                                                                                                         50.0
                                                                                                                 42.0
                         3
                             138.0
                                    134.0
                                            119.0
                                                   119.0
                                                           118.0
                                                                  129.0
                                                                          121.0
                                                                                 139.0
                                                                                         130.0
                                                                                                110.0
                                                                                                        123.0
                                                                                                               122.0
                                                   155.0
                                                           139.0
                             160.0
                                    151.0
                                            138.0
                                                                  133.0
                                                                          168.0
                                                                                 102.0
                                                                                         135.0
                                                                                                137.0
                                                                                                        126.0
                                                                                                               134.0
                         5
                             120.0
                                    112.0
                                            125.0
                                                   107.0
                                                           111.0
                                                                  125.0
                                                                          118.0
                                                                                 106.0
                                                                                          97.0
                                                                                                109.0
                                                                                                        104.0
                                                                                                               127.0
                                ...
                                        ...
                                               ...
                                                       ...
                                                              ...
                                                                      ...
                                                                                                    ...
                                                                                                           ...
                                                                             ...
                                                                                     ...
                                                                                            ...
                                                                                                                   ...
                       268
                              52.0
                                     54.0
                                             34.0
                                                    48.0
                                                            51.0
                                                                   43.0
                                                                           38.0
                                                                                  37.0
                                                                                          47.0
                                                                                                 50.0
                                                                                                         52.0
                                                                                                                 40.0
                       269
                             139.0
                                    132.0
                                            124.0
                                                   148.0
                                                          136.0
                                                                  133.0
                                                                          144.0
                                                                                 133.0
                                                                                         122.0
                                                                                                139.0
                                                                                                        130.0
                                                                                                               127.0
                       270
                             139.0
                                    154.0
                                            126.0
                                                   119.0
                                                           133.0
                                                                  149.0
                                                                          155.0
                                                                                 125.0
                                                                                         143.0
                                                                                                132.0
                                                                                                        128.0
                                                                                                               127.0
                                                           122.0
                                                                          120.0
                                                                                                               129.0
                       271
                             129.0
                                    101.0
                                            114.0
                                                   114.0
                                                                  117.0
                                                                                 102.0
                                                                                         101.0
                                                                                                109.0
                                                                                                        127.0
                       272
                              52.0
                                     48.0
                                                            45.0
                                                                   47.0
                                                                           50.0
                                                                                  48.0
                                                                                                  56.0
                                             36.0
                                                    51.0
                                                                                          53.0
                                                                                                         40.0
                                                                                                                 37.0
```

272 rows × 12 columns

```
In [14]: | no_record.isnull().sum()
Out[14]:
          YEARMO
          18-07
                    6
          18-08
                    9
          18-09
                    8
          18-10
                    7
          18-11
                    8
                    9
          18-12
          19-01
                    9
          19-02
                    8
          19-03
                    7
                    7
          19-04
                    9
          19-05
          19-06
                    8
          dtype: int64
```

```
In [15]: arr= [ ]
    for i in no_record.index:
        if no_record.loc[i].isnull().any():
            arr.append(i)
        arr

Out[15]: [11, 31, 44, 76, 85, 92, 117, 193, 206, 211, 218, 252]
In [16]: data.drop(arr, inplace= True)
```

Two dataframes will be created to hold the metrics for the pre-trial and trial periods

```
In [20]: trial= data[data.index.get_level_values('YEARMO').isin(['19-03','19-04'])]
    pre_trial= data[~data.index.get_level_values('YEARMO').isin(['19-02', '19-03',
```

Now, we will create a function that will calculate the stores that is correlated to the trial stores. The stores will be correlated on the 'tot sales' and 'tot customers' columns.

```
In [21]: def calculate_corr(store):
    corr= [ ]
    data1= pre_trial[['tot_sales', 'tot_customers']]
    for x in data1.index:
        table= data1.loc[store].corrwith(data1.loc[x[0]])
        corr.append(table)
    df1= pd.DataFrame(corr)
    df1.index= data1.index
    df1.drop_duplicates(inplace= True)
    df1.index= [s[0] for s in df1.index]
    df1.index.name= 'store_number'
    df1= df1.abs()
    df1['avg_score']= df1.mean(axis= 1) # to hold the mean correlation score
    return df1
```

# Finding stores correlated to store 77

```
In [22]: corr77= calculate_corr(77)
```

In [23]: corr77

Out[23]:

tot_sales	tot_customers	avg_score
-----------	---------------	-----------

store_number			
1	0.138045	0.292531	0.215288
2	0.092418	0.226371	0.159395
3	0.383045	0.722707	0.552876
4	0.529948	0.526731	0.528340
5	0.253424	0.172905	0.213164
268	0.375997	0.452769	0.414383
269	0.410675	0.406491	0.408583
270	0.110342	0.250728	0.180535
271	0.214199	0.023417	0.118808
272	0.247381	0.105710	0.176545

260 rows × 3 columns

Out[24]:

#### tot\_sales tot\_customers avg\_score

store_number			
77	1.000000	1.000000	1.000000
233	0.880004	0.994132	0.937068
84	0.777507	0.876067	0.826787
41	0.836940	0.799126	0.818033
115	0.715956	0.839229	0.777592
167	0.725318	0.814820	0.770069
242	0.735269	0.760095	0.747682
35	0.658044	0.778959	0.718502
254	0.542027	0.881578	0.711802
71	0.615592	0.790893	0.703242

# From the table above, it is clearly shown that store 233 correlates most with the trial store 77

## Visualising this....

```
In [25]: corr_table.plot(kind= 'bar')
Out[25]: <AxesSubplot:xlabel='store_number'>
            1.0
                                                         tot sales
                                                         tot_customers
                                                         avg_score
            0.8
            0.6
            0.4
            0.2
            0.0
                            8
                                  41
                                                  242
                                                       쏬
                                            167
```

store\_number

Checking to see if there is any significant difference between the stores before the trial period...

```
In [26]:
    from scipy.stats import ttest_ind
    def pre_significance_test(sig_df1, sig_df2):
        #Conducts a ttest for the pre trial period
        "" Null hypothesis: There is no significant difference between the two Alternate hypothesis: There is a significant difference between the two Alpha= 0.05""

        arr=[]
        for i in pre_trial.columns:
            tab= ttest_ind(sig_df1[i], sig_df2[i])
            arr.append(tab)
        temp_df= pd.DataFrame(arr)
        temp_df.index= pre_trial.columns
        return temp_df
```

```
In [27]: pre_significance_test(pre_trial.loc[77], pre_trial.loc[233])
```

#### Out[27]:

	statistic	pvalue
tot_sales	0.191110	0.850844
tot_customers	-0.034001	0.973297
txn_per_customer	0.523638	0.607708

4 - 42 - 42 -

The pvalue is greater than 0.05 so therefore, there is no significant difference between stores 77 and 233 for the pre-trial period. This confirms that stores 77 and 233 are identical.

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).

warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).

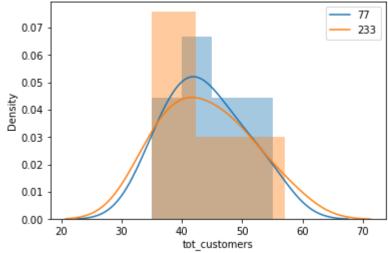


```
In [29]: sns.distplot(pre_trial.loc[77]['tot_customers'])
    sns.distplot(pre_trial.loc[233]['tot_customers'])
    plt.legend(['77', '233'])
    plt.title('Distribution plot of customers of stores 77 and 233 before the trial plt.show()
```

warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).





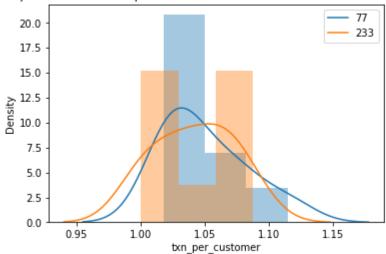
```
In [30]: sns.distplot(pre_trial.loc[77]['txn_per_customer'])
    sns.distplot(pre_trial.loc[233]['txn_per_customer'])
    plt.legend(['77', '233'])
    plt.title('Distribution plot of transaction per customers of stores 77 and 233
    plt.show()
```

warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).

warnings.warn(msg, FutureWarning)





Checking to see if there is any significant difference between both stores during the trial period.......

```
In [31]:
    def trial_significance_test(sig_df3, sig_df4):
        #Conducts a ttest for the last two months of the trial period i.e (19-03 and '''Null hypothesis: There is no significant difference between the two stown Alternate hypothesis: There is a significant difference between the two stown Alpha = 0.05 '''

arr2=[]
    for i in trial.columns:
        tab= ttest_ind(sig_df3[i], sig_df4[i], alternative= 'greater')
        arr2.append(tab)
    temp_df1= pd.DataFrame(arr2)
    temp_df1.index= trial.columns
    return temp_df1
```

In [33]: trial\_significance\_test(post\_trial.loc[77], post\_trial.loc[233])

#### Out[33]:

	statistic	pvalue
tot_sales	4.267336	0.025384
tot_customers	2.586131	0.061309
txn per customer	0.332434	0.385585

The pvalue for the total sales is less than 0.05 so, the alternate hypothesis that the total sales for the trial store is greater than that of the control store is acceped. For the other metrics; total customers and transaction per customer, the null hypothesis is accepted that the mean values for the total customers and transaction per customer is identical.......

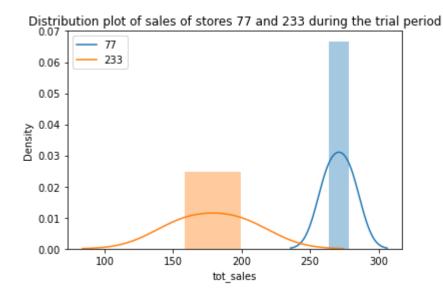
# Visualising the difference.....

```
In [34]: sns.distplot(trial.loc[77]['tot_sales'])
    sns.distplot(trial.loc[233]['tot_sales'])
    plt.legend(['77', '233'])
    plt.title('Distribution plot of sales of stores 77 and 233 during the trial per
    plt.show()
```

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).

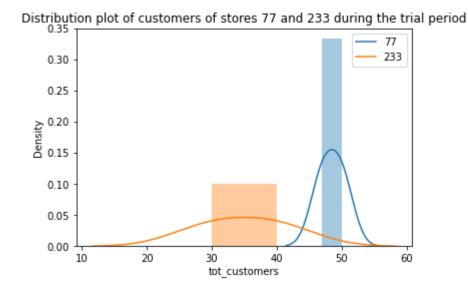
warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).



warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).

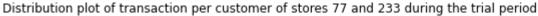


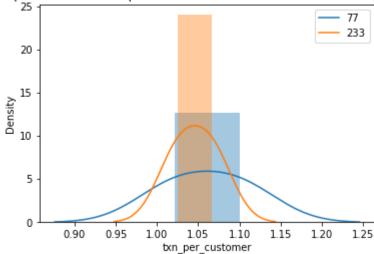
```
In [36]: sns.distplot(trial.loc[77]['txn_per_customer'])
    sns.distplot(trial.loc[233]['txn_per_customer'])
    plt.legend(['77', '233'])
    plt.title('Distribution plot of transaction per customer of stores 77 and 233 plt.show()
```

warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).

warnings.warn(msg, FutureWarning)





The visualization confirms the hypothesis test conducted. There is a significant difference between the total sales for stores 77 and 233. The difference of the total customers between the two stores are somewhat significant and there is no significant difference between the transaction per customers between both stores

Store 77 only perform well in terms of total sales but not in terms of total customers and transaction per customers.

# Finding stores correlated to store 86

```
In [37]: |corr86= calculate_corr(86)
In [38]:
          corr86
Out[38]:
                          tot_sales tot_customers avg_score
            store_number
                           0.483857
                                          0.486520
                                                     0.485188
                       2
                          0.237462
                                          0.188549
                                                     0.213006
                           0.232796
                                          0.273946
                                                     0.253371
                           0.048187
                                          0.294060
                                                     0.171123
                          0.001803
                                          0.387089
                                                     0.194446
                     268
                           0.417161
                                          0.082707
                                                     0.249934
                     269
                          0.672849
                                          0.098401
                                                     0.385625
                     270
                           0.668908
                                          0.774747
                                                     0.721827
                     271
                           0.330326
                                          0.099780
                                                     0.215053
                     272
                          0.061332
                                          0.337759
                                                     0.199545
           260 rows × 3 columns
In [39]:
           corr_table1= corr86.sort_values(by= 'avg_score', ascending= False).head(10)
           corr_table1
Out[39]:
                          tot_sales tot_customers avg_score
            store_number
                           1.000000
                                          1.000000
                                                     1.000000
                       86
                      155
                           0.885236
                                          0.930845
                                                     0.908040
                       23
                          0.707142
                                          0.885187
                                                     0.796165
                     260
                           0.668425
                                          0.833410
                                                     0.750918
                       27
                           0.753940
                                          0.724051
                                                     0.738995
                           0.799645
                                                     0.733959
                     214
                                          0.668273
                     270
                          0.668908
                                          0.774747
                                                     0.721827
                     240
                           0.814900
                                          0.618404
                                                     0.716652
                      120
                           0.821346
                                          0.608472
                                                     0.714909
                          0.734499
                                          0.597523
                                                     0.666011
```

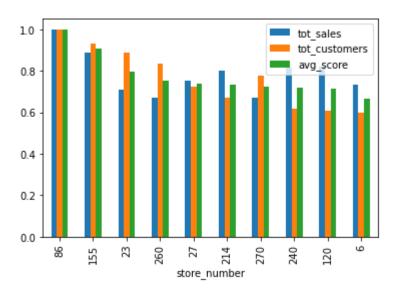
# From the table above, it is clearly shown that store 155

# correlates most with the trial store 86

## Visualising this....

In [40]: corr\_table1.plot(kind= 'bar')

Out[40]: <AxesSubplot:xlabel='store\_number'>



Checking to see if there is any significant difference between the stores before the trial period...

In [41]: pre\_significance\_test(pre\_trial.loc[86], pre\_trial.loc[155])

#### Out[41]:

	statistic	pvalue
tot_sales	-0.913340	0.374622
tot_customers	0.045549	0.964234
txn per customer	-1.569054	0.136198

warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).

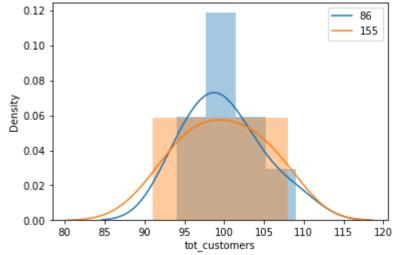


```
In [43]: sns.distplot(pre_trial.loc[86]['tot_customers'])
    sns.distplot(pre_trial.loc[155]['tot_customers'])
    plt.legend(['86', '155'])
    plt.title('Distribution plot of customers of stores 86 and 155 before the trial plt.show()
```

warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).





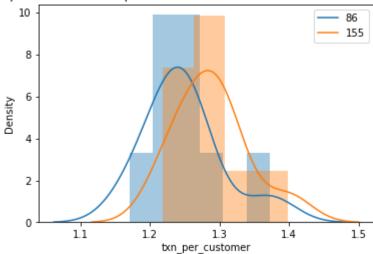
```
In [44]: sns.distplot(pre_trial.loc[86]['txn_per_customer'])
    sns.distplot(pre_trial.loc[155]['txn_per_customer'])
    plt.legend(['86', '155'])
    plt.title('Distribution plot of transaction per customers of stores 86 and 155
    plt.show()
```

warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).

warnings.warn(msg, FutureWarning)





Lets check if there is any significant difference between both stores for the period during the trial....

#### Out[45]:

	statistic	pvalue
tot_sales	1.234512	0.171189
tot_customers	2.414953	0.068538
txn per customer	-1.074767	0.802535

The pvalue for the total sales, total customers and transaction per customer is greater than 0.05 so the null hypothesis is accepted that the mean values for the total sales, total customers and transaction

#### per customer is identical for both stores.......

# Visualising the difference.....

```
In [46]: sns.distplot(trial.loc[86]['tot_sales'])
    sns.distplot(trial.loc[155]['tot_sales'])
    plt.legend(['86', '155'])
    plt.title('Distribution plot of sales of stores 86 and 155 during the trial per
    plt.show()
```

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).

warnings.warn(msg, FutureWarning)

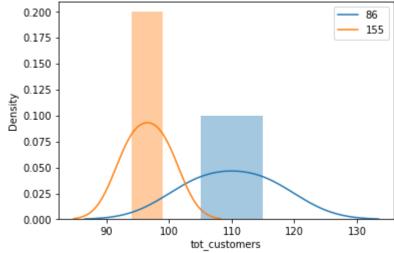
C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).



warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).





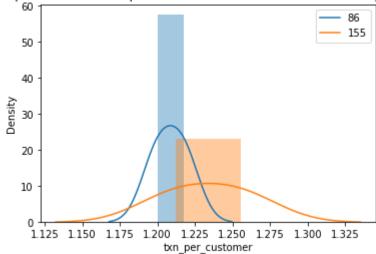
```
In [48]: sns.distplot(trial.loc[86]['txn_per_customer'])
    sns.distplot(trial.loc[155]['txn_per_customer'])
    plt.legend(['86', '155'])
    plt.title('Distribution plot of transaction per customer of stores 86 and 155 plt.show()
```

warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).

warnings.warn(msg, FutureWarning)





The visualization confirms the hypothesis test conducted. The difference between the total customers for stores 86 and 155 is somewhat significant. There is no significant difference between the transaction per customers and total sales for both stores.

Store 86 only perform well in terms of total customers but not in terms of total sales and transaction per customers.

# Finding stores correlated to store 88...

```
In [49]: corr88= calculate_corr(88)
```

In [50]: corr88

Out[50]:

tot_sales	tot_customers	avg_score
-----------	---------------	-----------

store_number				
1	0.657299	0.343999	0.500649	
2	0.202082	0.127006	0.164544	
3	0.371783	0.533943	0.452863	
4	0.407844	0.351343	0.379593	
5	0.310585	0.280154	0.295370	
268	0.060247	0.717665	0.388956	
269	0.145038	0.060771	0.102905	
270	0.636188	0.131879	0.384034	
271	0.017985	0.255827	0.136906	
272	0.505246	0.094311	0.299778	

260 rows × 3 columns

Out[51]:

tot sales	tot_customers	avg score

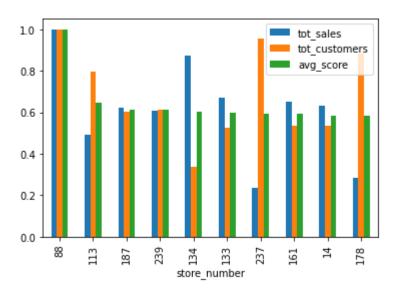
store_number			
88	1.000000	1.000000	1.000000
113	0.489780	0.797347	0.643564
187	0.619833	0.604224	0.612029
239	0.608617	0.613465	0.611041
134	0.870708	0.338051	0.604379
133	0.669638	0.524265	0.596951
237	0.236508	0.953220	0.594864
161	0.653020	0.534989	0.594004
14	0.632443	0.533647	0.583045
178	0.284718	0.880290	0.582504

# From the table above, it is clearly shown that stores 113, 134, 237, 178 correlates most with the trial store 88.

## Visualising this.....

In [52]: corr\_table2.plot(kind= 'bar')

Out[52]: <AxesSubplot:xlabel='store\_number'>



A statistical test(t\_test) will be conducted to show which of these stores is most identical to the trial store 88 or has the same distribution with the trial store.

The null hypothesis is that the stores are identical while the null hypothesis is that the stores are different.

Conducting the t-test for stores 88, 113......

In [53]: pre\_significance\_test(pre\_trial.loc[88], pre\_trial.loc[113])

Out[53]:

	statistic	pvalue
tot_sales	13.941365	2.277913e-10
tot_customers	11.014370	7.047736e-09
txn_per_customer	-3.890683	1.299023e-03

The pvalue for all metrics for stores 88 and 113 is lesser than 0.05, so the null hypothesis is rejected and stores 88 and 113 are not identical.

Conducting the ttest for stores 88 and 134....

In [54]: pre\_significance\_test(pre\_trial.loc[88], pre\_trial.loc[134])

#### Out[54]:

	statistic	pvalue
tot_sales	48.786741	7.784755e-19
tot_customers	39.250045	2.458734e-17
txn_per_customer	9.468581	5.839998e-08

The pvalue for all metrics for stores 88 and 134 is lesser than 0.05, so the null hypothesis is rejected and stores 88 and 134 are not identical.

Conducting the ttest for stores 88 and 237....

In [55]: pre\_significance\_test(pre\_trial.loc[88], pre\_trial.loc[237])

#### Out[55]:

	statistic	pvalue
tot_sales	0.992560	0.335699
tot_customers	-0.179154	0.860066
txn_per_customer	1.532020	0.145050

The pvalue for all metrics for stores 88 and 237 is greaterer than 0.05, so we fail to reject the null hypothesis. This confirms that stores 88 and 237 are identical.

Conducting the ttest for stores 88 and 178....

In [56]: pre\_significance\_test(pre\_trial.loc[88], pre\_trial.loc[178])

#### Out[56]:

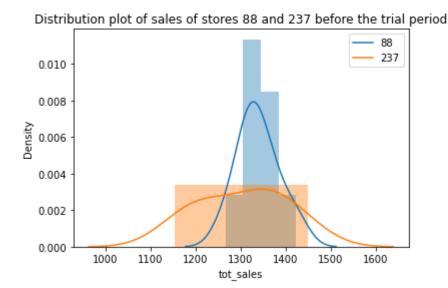
	statistic	pvalue
tot_sales	13.880579	2.430580e-10
tot_customers	9.200267	8.646888e-08
txn_per_customer	-2.061957	5.584234e-02

The pvalue for all metrics for stores 88 and 237 is greaterer than 0.05, so we fail to reject the null hypothesis. This confirms that stores 88 and 237 are identical.

Of all the stores correlated to store 88, store 237 correlates the most, so we will use this in our analysis.

warnings.warn(msg, FutureWarning)

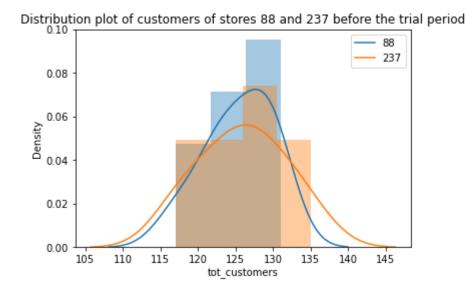
C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).



```
In [58]: sns.distplot(pre_trial.loc[88]['tot_customers'])
    sns.distplot(pre_trial.loc[237]['tot_customers'])
    plt.legend(['88', '237'])
    plt.title('Distribution plot of customers of stores 88 and 237 before the trial plt.show()
```

warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).



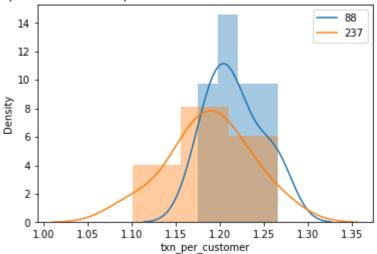
```
In [59]: sns.distplot(pre_trial.loc[88]['txn_per_customer'])
    sns.distplot(pre_trial.loc[237]['txn_per_customer'])
    plt.legend(['88', '237'])
    plt.title('Distribution plot of transaction per customers of stores 88 and 237
    plt.show()
```

warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).

warnings.warn(msg, FutureWarning)





Lets check if there is any significant difference between both stores for the period during the trial....

In [60]: trial\_significance\_test(trial.loc[88], trial.loc[237])

Out[60]:

	statistic	pvalue
tot_sales	13.268006	0.002816
tot_customers	3.781177	0.031684
txn per customer	60.558224	0.000136

The pvalue for the total sales, total customers and transaction per customer is lesser than 0.05 so the null hypothesis is rejected that the mean values for the total

sales, total customers and transaction per customer is identical for both stores. This shows that the metrics for the trial store is greater than that of the control store.......

### Visualising the difference.....

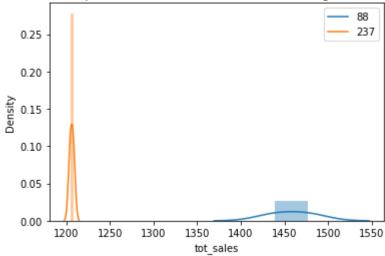
```
In [61]: sns.distplot(trial.loc[88]['tot_sales'])
    sns.distplot(trial.loc[237]['tot_sales'])
    plt.legend(['88', '237'])
    plt.title('Distribution plot of sales of stores 88 and 237 during the trial per
    plt.show()
```

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).

warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).

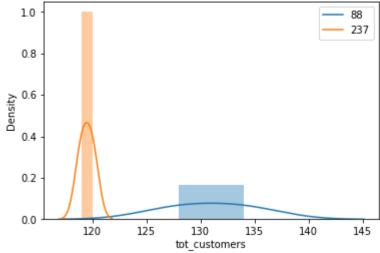




warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).





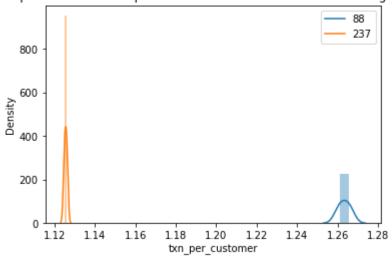
```
In [63]: sns.distplot(trial.loc[88]['txn_per_customer'])
    sns.distplot(trial.loc[237]['txn_per_customer'])
    plt.legend(['88', '237'])
    plt.title('Distribution plot of transaction per customer of stores 88 and 237
    plt.show()
```

warnings.warn(msg, FutureWarning)

C:\Users\Ceejay\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu tureWarning: `distplot` is a deprecated function and will be removed in a fut ure version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for h istograms).

warnings.warn(msg, FutureWarning)

Distribution plot of transaction per customer of stores 88 and 237 during the trial period



The visualization confirms the hypothesis test conducted. The difference between the total customers for stores 86 and 155 is greatly significant.

Store 88 does better than its relative control store 237 for all metrics.

## Conclusion

- The best performing trial store is store 88 since it does better in sales, customers and transaction per customer than its related control store.
- The worst performing trial store is store 86, as it does worse in sales and transaction per customer than its related control store.
- The trial carried out in store 88 should be emulated by other trial stores as it is the most effective.