TASK 2Experimentation and uplift testing

```
#imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

from plotly.offline import init_notebook_mode, iplot
init_notebook_mode(connected=True)
import plotly.offline as offline
offline.init_notebook_mode()
import cufflinks as cf
cf.go_offline()

#reading data
data=pd.read_csv("QVI_data.csv");
data.head(2)
```

```
   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

                                PROD_NAME  PROD_QTY  TOT_SALES
PACK_SIZE  \
0  Natural Chip        Compny SeaSalt175g         2        6.0
175
1   Red Rock Deli Chikn&Garlic Aioli 150g         1        2.7
150

     BRAND              LIFESTAGE PREMIUM_CUSTOMER
0  NATURAL  YOUNG SINGLES/COUPLES          Premium
1      RRD  YOUNG SINGLES/COUPLES       Mainstream
```

```
data['DATE']=pd.to_datetime(data['DATE'])

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264834 entries, 0 to 264833
Data columns (total 12 columns):
LYLTY_CARD_NBR      264834 non-null int64
DATE                264834 non-null datetime64[ns]
STORE_NBR           264834 non-null int64
TXN_ID              264834 non-null int64
PROD_NBR            264834 non-null int64
PROD_NAME           264834 non-null object
PROD_QTY            264834 non-null int64
```

```
TOT_SALES           264834 non-null float64
PACK_SIZE           264834 non-null int64
BRAND               264834 non-null object
LIFESTAGE           264834 non-null object
PREMIUM_CUSTOMER    264834 non-null object
dtypes: datetime64[ns](1), float64(1), int64(6), object(4)
memory usage: 24.2+ MB
```

```
data['YEARMONTH']=[s.year*100+s.month for s in data['DATE']]
```

```
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


        YEARMONTH
0          201810
1          201809
2          201903
3          201903
4          201811
...           ...
264829     201812
264830     201810
264831     201810
264832     201810
264833     201812

[264834 rows x 13 columns]
```

METRICS UNDER CONSIDERATION:

- Monthly overall sales revenue

- Monthly number of customers

- Monthly number of transactions per customer

```
metrics=data.groupby(['STORE_NBR','YEARMONTH']).agg({'TOT_SALES':'sum'
,'LYLTY_CARD_NBR':'nunique','TXN_ID':'nunique','PROD_QTY':'sum'})
metrics['PRICE_PER_UNIT']=metrics['TOT_SALES']/metrics['PROD_QTY']
metrics['CHIP_PER_TXN']=metrics['PROD_QTY']/metrics['TXN_ID']
```

```python
metrics=metrics.rename(columns={'LYLTY_CARD_NBR':'CUSTOMERS'})
metrics['TXN_PER_CUST']=metrics['TXN_ID']/metrics['CUSTOMERS']
metrics.drop(['TXN_ID'],axis=1,inplace=True)

full=metrics.copy()

#taking data before 2019-02 into consideration
trial=[]
for i in metrics.index:
    if(i[1]>=201902):
        if(i[1]<=201904):
            trial.append(metrics.loc[i])
        metrics.drop(i,inplace=True)
trial=pd.DataFrame(trial)

#taking data after 2019-02 into trial dataframe
trial.index.name=('IDX')
k=0
trial['STORE_NBR']=0
trial['MONTHYEAR']=0
for (i,j) in trial.reset_index()['IDX']:
    trial['STORE_NBR'].iloc[k]=i
    trial['MONTHYEAR'][k]=j
    k=k+1
trial=trial.set_index(['STORE_NBR','MONTHYEAR'])

metrics
```

```
                     TOT_SALES  CUSTOMERS  PROD_QTY  PRICE_PER_UNIT  \
STORE_NBR YEARMONTH                                                   
1         201807         206.9         49        62        3.337097   
          201808         176.1         42        54        3.261111   
          201809         278.8         59        75        3.717333   
          201810         188.1         44        58        3.243103   
          201811         192.6         46        57        3.378947   
...                        ...        ...       ...             ...   
272       201809         304.7         32        71        4.291549   
          201810         430.6         44        99        4.349495   
          201811         376.2         41        87        4.324138   
          201812         403.9         47        89        4.538202   
          201901         423.0         46        96        4.406250   

                     CHIP_PER_TXN  TXN_PER_CUST  
STORE_NBR YEARMONTH                              
1         201807         1.192308      1.061224  
          201808         1.255814      1.023810  
          201809         1.209677      1.050847  
          201810         1.288889      1.022727  
          201811         1.212766      1.021739  
...                           ...           ...  
```

```
272       201809        1.972222      1.125000
          201810        1.980000      1.136364
          201811        1.933333      1.097561
          201812        1.893617      1.000000
          201901        1.920000      1.086957

[1848 rows x 6 columns]
```

Funtions to find correlation and magnitude of any store wih another store

```python
def calcCorr(store):
    '''
    input=store number which is to be compared
    output=dataframe with corelation coefficient values
    '''
    a=[]
    metrix=metrics[['TOT_SALES','CUSTOMERS']]#add metrics as required e.g. ,'TXN_PER_CUST'
    for i in metrix.index:
        a.append(metrix.loc[store].corrwith(metrix.loc[i[0]]))
    df= pd.DataFrame(a)
    df.index=metrix.index
    df=df.drop_duplicates()
    df.index=[s[0] for s in df.index]
    df.index.name="STORE_NBR"
    return df

def standardizer(df):
    '''
    input=dataframe with metrics
    output=dataframe with mean of the metrics in a new column
    '''
    df=df.abs()
    df['MAGNITUDE']=df.mean(axis=1)
    return df
```

Store 77

Finding stores corelated to store 77

```python
corr77=calcCorr(77)

corr77.head(3)
```

```
           TOT_SALES  CUSTOMERS
STORE_NBR
```

```
1            0.075218   0.322168
2           -0.263079  -0.572051
3            0.806644   0.834207
```

```
corr77=standardizer(corr77)
corr77
```

```
           TOT_SALES  CUSTOMERS  MAGNITUDE
STORE_NBR
1           0.075218   0.322168   0.198693
2           0.263079   0.572051   0.417565
3           0.806644   0.834207   0.820426
4           0.263300   0.295639   0.279469
5           0.110652   0.370659   0.240655
...              ...        ...        ...
268         0.344757   0.369517   0.357137
269         0.315730   0.474293   0.395011
270         0.315430   0.131259   0.223345
271         0.355487   0.019629   0.187558
272         0.117622   0.223217   0.170420

[266 rows x 3 columns]
```

```
corr77=corr77.sort_values(['MAGNITUDE'],ascending=False).dropna()
```

```
corr77
```

```
           TOT_SALES  CUSTOMERS  MAGNITUDE
STORE_NBR
77          1.000000   1.000000   1.000000
233         0.903774   0.990358   0.947066
119         0.867664   0.983267   0.925466
71          0.914106   0.754817   0.834461
3           0.806644   0.834207   0.820426
...              ...        ...        ...
256         0.014245   0.047863   0.031054
159         0.001655   0.054404   0.028030
260         0.016618   0.027446   0.022032
194         0.010182   0.032053   0.021117
166         0.005875   0.012896   0.009386

[263 rows x 3 columns]
```

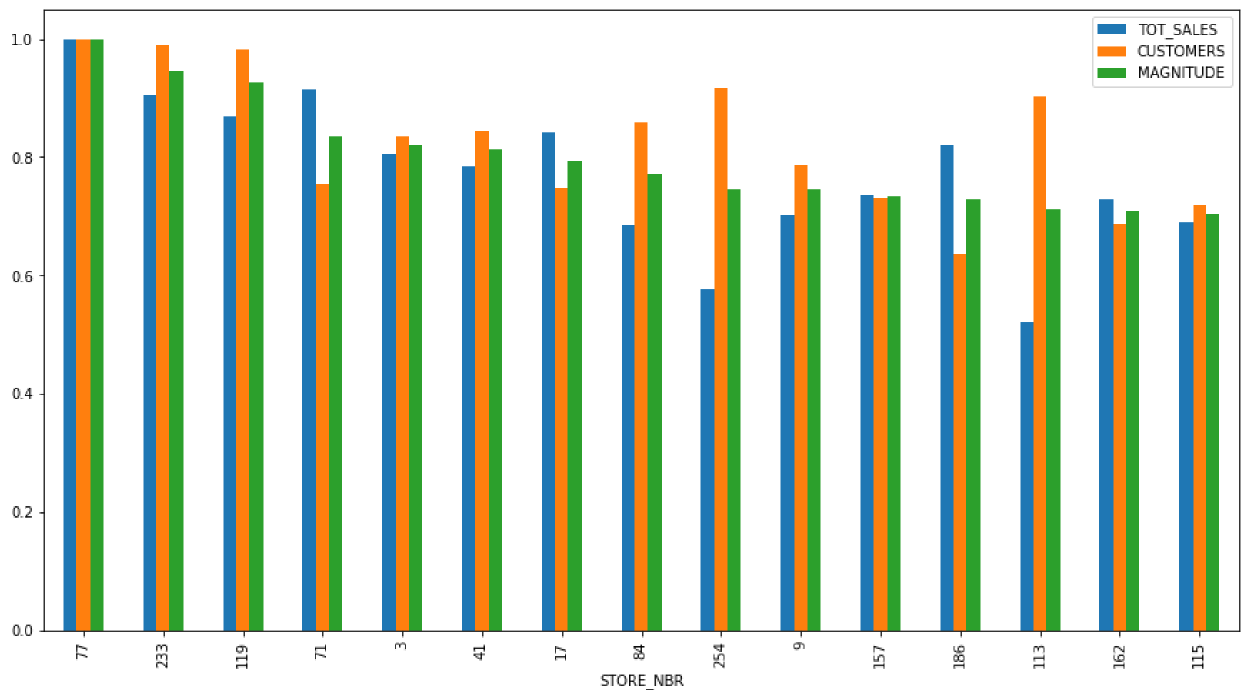
**shows that stores 233,119,71 are the most correlated to store 77

Selecting 233 as control store as it has max correlation

Visualizing ...

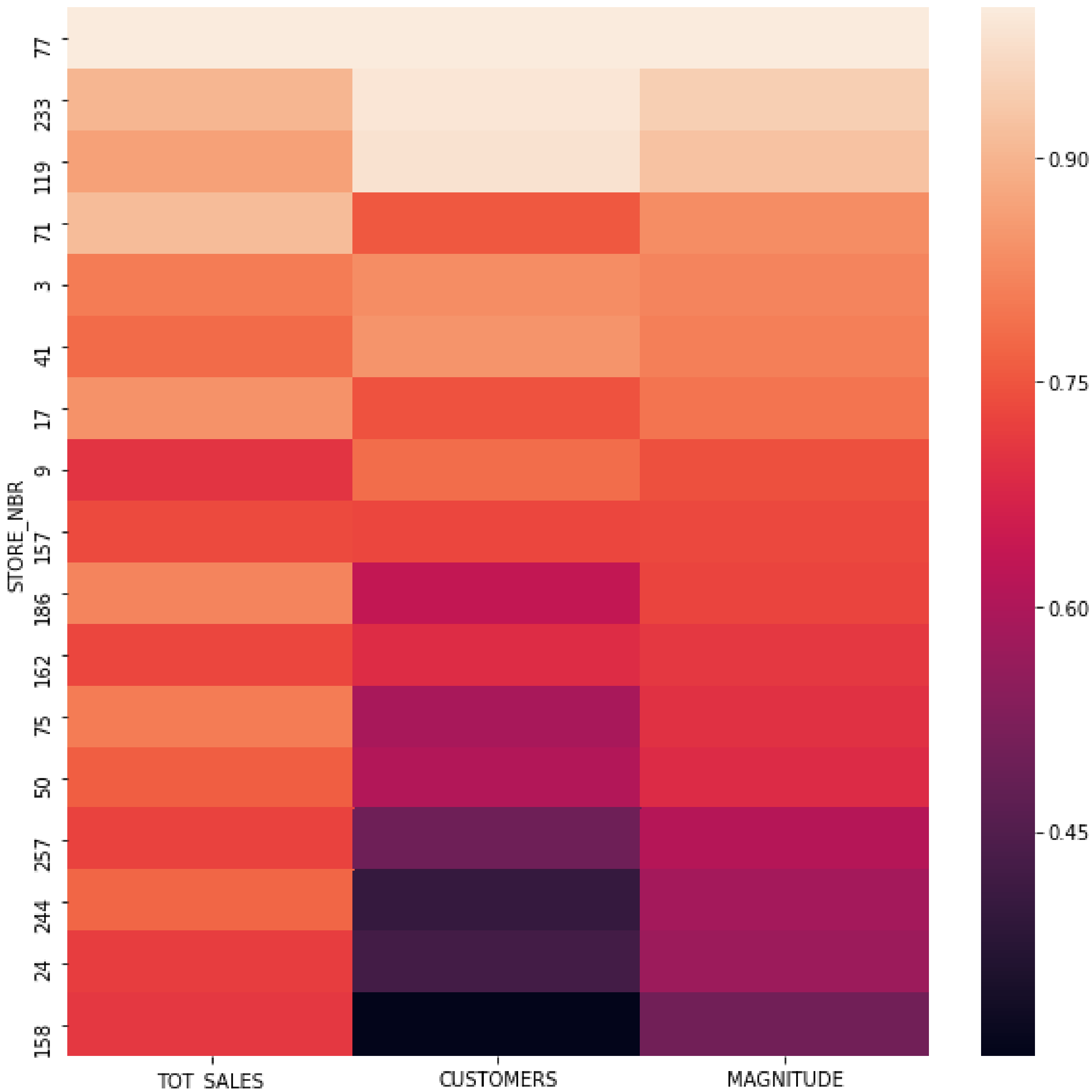
```
#Taking 0.7 as threshold corelation
corr77[(corr77.MAGNITUDE.abs()>0.7)].plot(kind='bar',figsize=(15,8))
```

```
<AxesSubplot:xlabel='STORE_NBR'>
```




```
plt.figure(figsize=(10,10))
sns.heatmap(corr77[corr77.TOT_SALES.abs()>0.7])
```

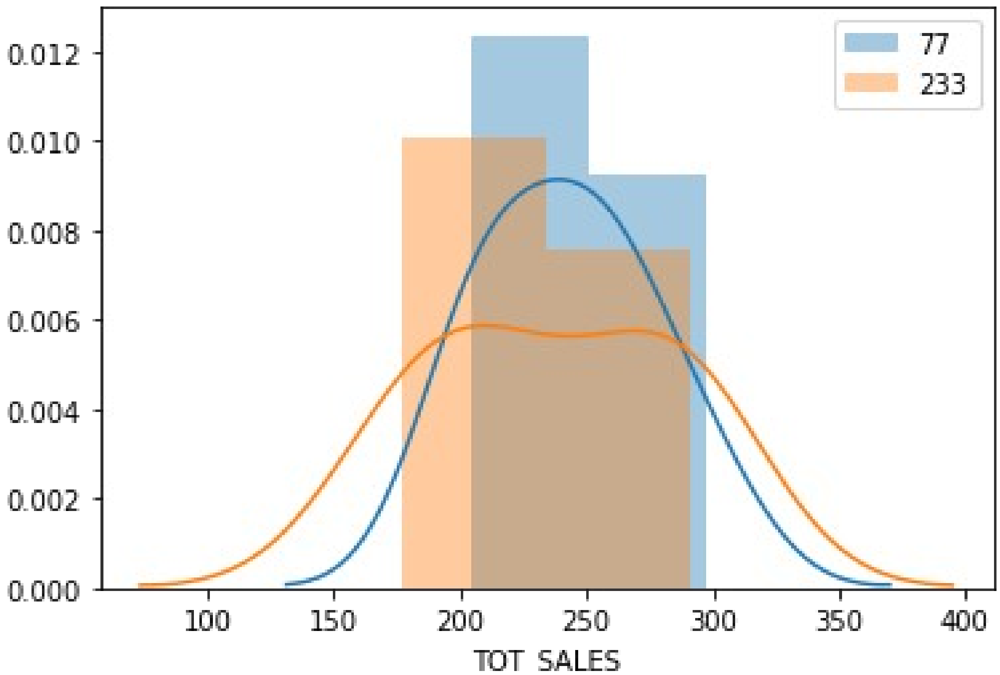
```
<AxesSubplot:ylabel='STORE_NBR'>
```



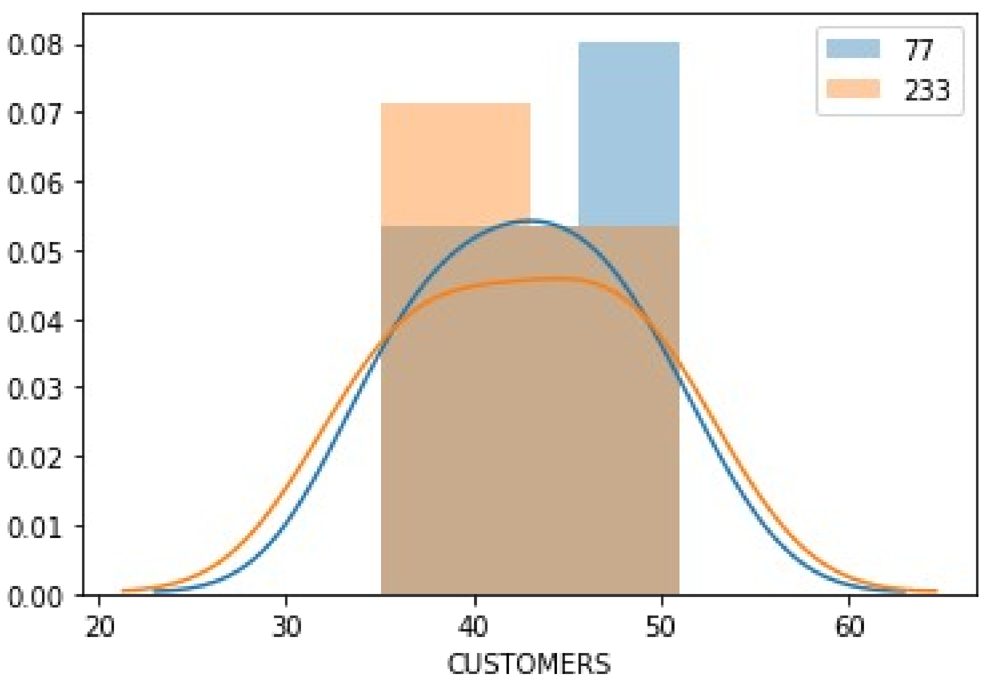
Taking the store 233 into consideration plotting different measure against those of store 77

```
sns.distplot(metrics.loc[77]['TOT_SALES'])
sns.distplot(metrics.loc[233]['TOT_SALES'])
plt.legend(labels=['77','233'])
```

```
<matplotlib.legend.Legend at 0x27644cae908>
```

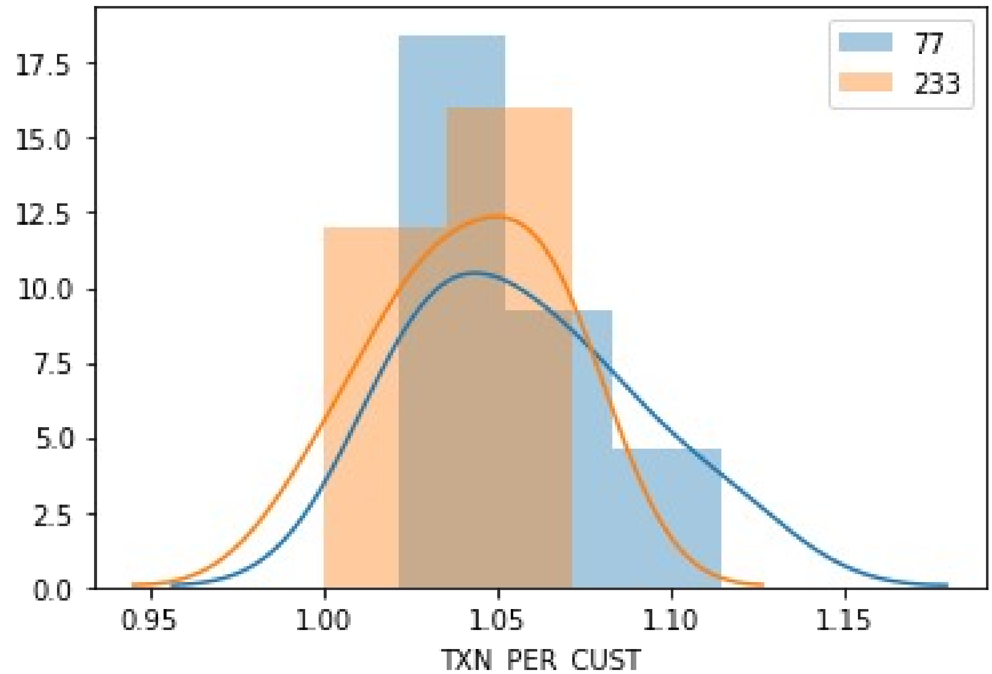



```
sns.distplot(metrics.loc[77]['CUSTOMERS'])
sns.distplot(metrics.loc[233]['CUSTOMERS'])
plt.legend(labels=['77','233'])

<matplotlib.legend.Legend at 0x27645037bc8>
```



```
sns.distplot(metrics.loc[77]['TXN_PER_CUST'])
sns.distplot(metrics.loc[233]['TXN_PER_CUST'])
plt.legend(labels=['77','233'])
```

```
<matplotlib.legend.Legend at 0x27644ea9308>
```



Since distributions of store 233 are similar to that of store 77, selecting store 233 as control store with max similarities to store 77

Calculating difference between scaled control sales and trial sales

Let null hypothesis be that both stores 77 ans 233 have no difference

```
from scipy.stats import ks_2samp,ttest_ind,t

# difference between control and trial sales
a=[]
for x in metrics.columns:
    a.append(ks_2samp(metrics.loc[77][x], metrics.loc[233][x]))
a=pd.DataFrame(a,index=metrics.columns)

a
```

	statistic	pvalue
TOT_SALES	0.285714	0.962704
CUSTOMERS	0.142857	1.000000

```
PROD_QTY          0.285714  0.962704
PRICE_PER_UNIT    0.285714  0.962704
CHIP_PER_TXN      0.285714  0.962704
TXN_PER_CUST      0.428571  0.575175
```

For pre trial period, since all of the p-values are high (say more than 0.05), we can't reject the null hypothesis

Assessment of trial

The trial period goes from the start of February 2019 to April 2019. We now want to see if there has been an uplift in overall chip sales.

Sampling march and april from the 3 months

```
b=[]
for x in trial.columns:
    b.append(ttest_ind(trial.loc[77][x].tail(2), trial.loc[233]
[x].tail(2)))
b=pd.DataFrame(b,index=metrics.columns)

b
```

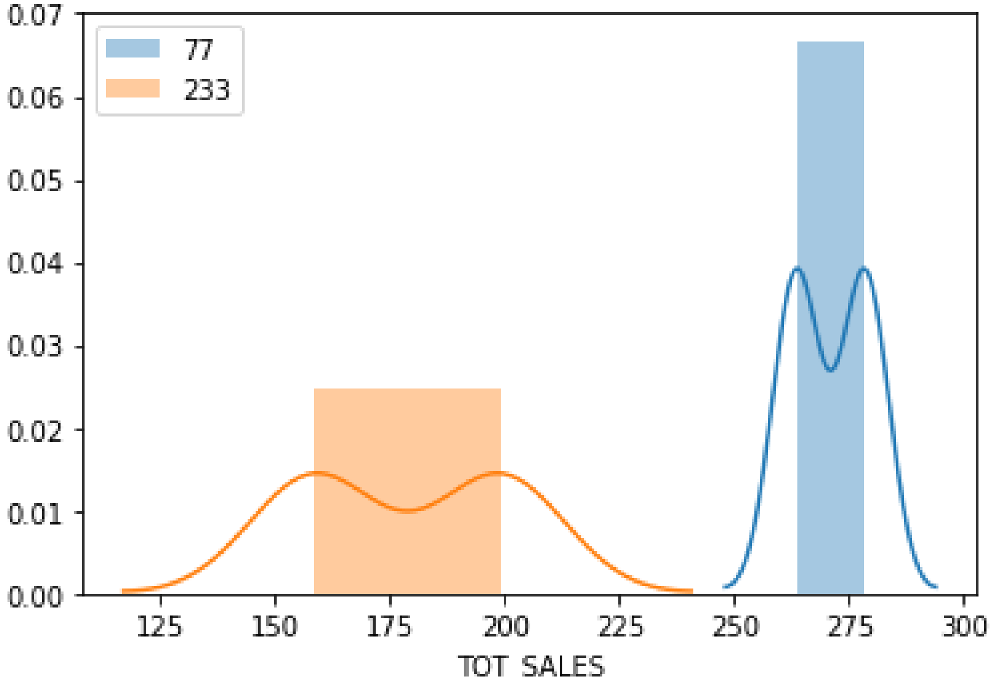
	statistic	pvalue
TOT_SALES	4.267336	0.050769
CUSTOMERS	2.586131	0.122618
PROD_QTY	4.043680	0.056063
PRICE_PER_UNIT	-0.634173	0.590828
CHIP_PER_TXN	1.785126	0.216165
TXN_PER_CUST	0.332434	0.771171

```
#critical value
t.ppf(0.95,df=7)

1.894578605061305
```

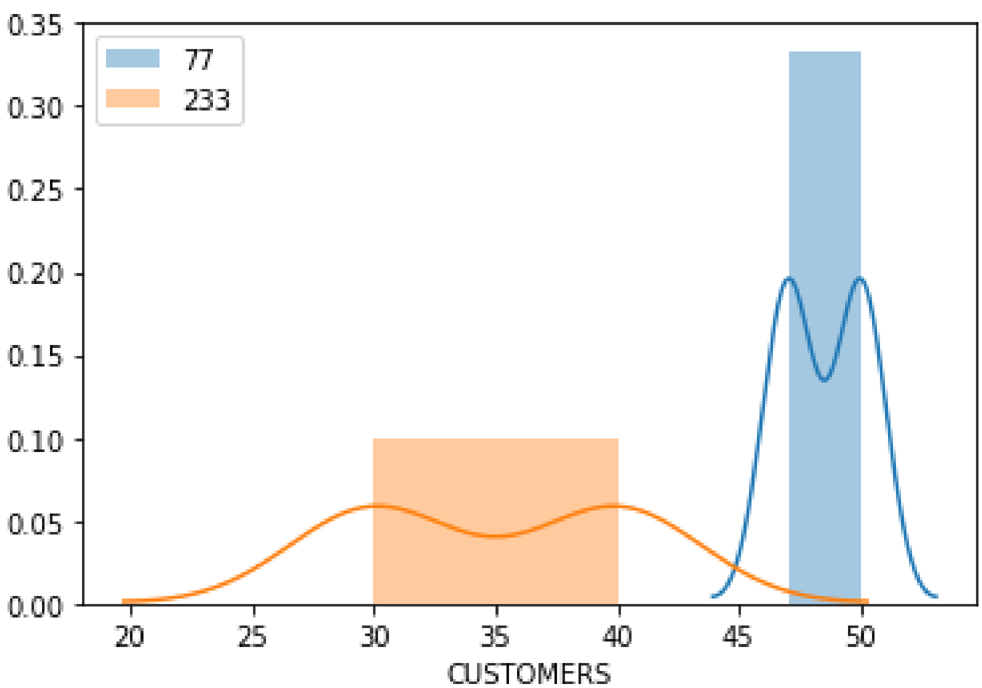
Since all of the p-values are high (say more than 0.05), we reject the null hypothesis i.e. there means are significantly different. We can observe that the t-value is much larger than the 95th percentile value of the t-distribution for March and April - i.e. the increase in sales in the trial store in March and April is statistically greater than in the control store.

Vizualizing means

```
sns.distplot(trial.loc[77]['TOT_SALES'].tail(2))
sns.distplot(trial.loc[233]['TOT_SALES'].tail(2))
plt.legend(labels=['77','233'])

<matplotlib.legend.Legend at 0x27660b0e408>
```




```
sns.distplot(trial.loc[77]['CUSTOMERS'].tail(2))
sns.distplot(trial.loc[233]['CUSTOMERS'].tail(2))
plt.legend(labels=['77','233'])

<matplotlib.legend.Legend at 0x276602204c8>
```



It can be visualized that the is a significant difference in the means, so trial store behavior(77) is different from control store (233).

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.

Store 86

Repeating same process for trial store 86

```
corr86=calcCorr(86)
```

```
corr86.head(3)
```

	TOT_SALES	CUSTOMERS
STORE_NBR		
1	0.445632	0.485831
2	-0.403835	-0.086161
3	-0.261284	-0.353786

```
corr86=standardizer(corr86)
corr86
```

	TOT_SALES	CUSTOMERS	MAGNITUDE
STORE_NBR			
1	0.445632	0.485831	0.465731
2	0.403835	0.086161	0.244998
3	0.261284	0.353786	0.307535
4	0.039035	0.169608	0.104322
5	0.235159	0.253229	0.244194
...	...	...	...
268	0.452182	0.034273	0.243228
269	0.697055	0.098587	0.397821
270	0.730679	0.767267	0.748973
271	0.527637	0.267393	0.397515
272	0.004926	0.353815	0.179371

```
[266 rows x 3 columns]
```

```
corr86=corr86.sort_values(['MAGNITUDE'],ascending=False).dropna()
```

```
corr86
```

	TOT_SALES	CUSTOMERS	MAGNITUDE
STORE_NBR			
86	1.000000	1.000000	1.000000
155	0.877882	0.942876	0.910379
23	0.784698	0.943559	0.864128

```
120          0.872693   0.815097   0.843895
114          0.734415   0.855339   0.794877
...               ...        ...        ...
91           0.019027   0.041271   0.030149
17           0.029793   0.030039   0.029916
131          0.028487   0.031142   0.029815
219          0.046653   0.004999   0.025826
234          0.010509   0.040306   0.025407

[263 rows x 3 columns]
```

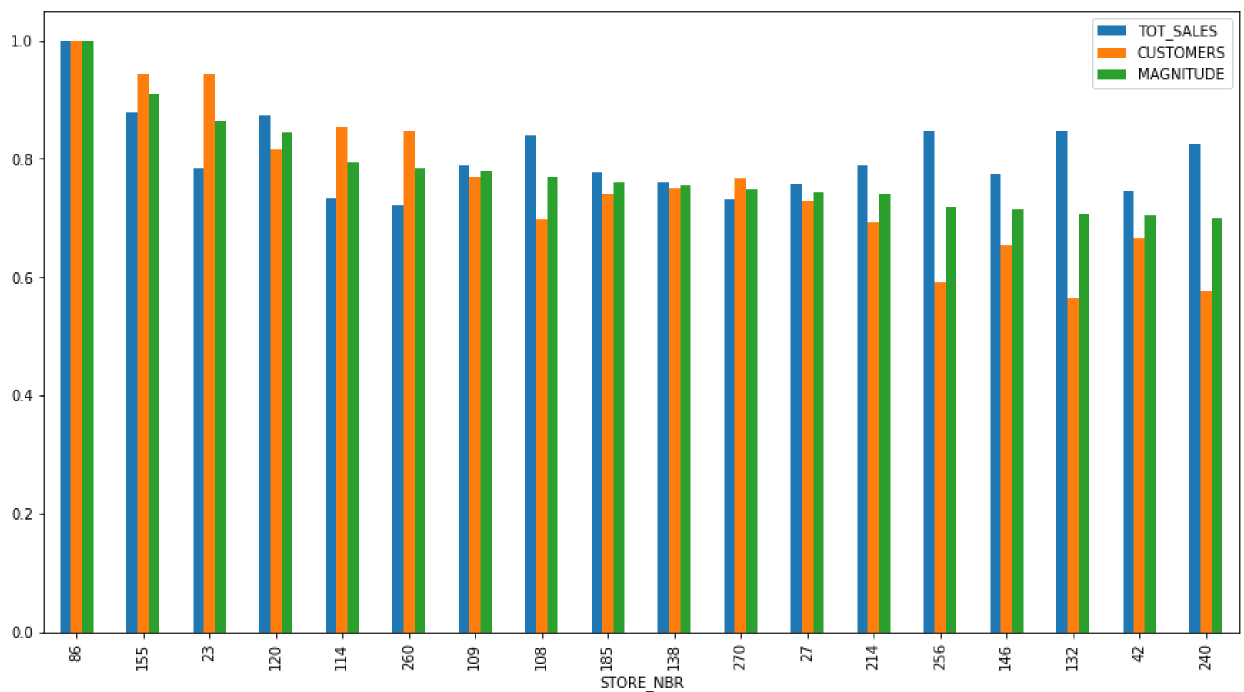
**shows that stores 155,23,120 are the most correlated to store 86

Selecting 155 as control store as it has max correlation

Visualizing ...

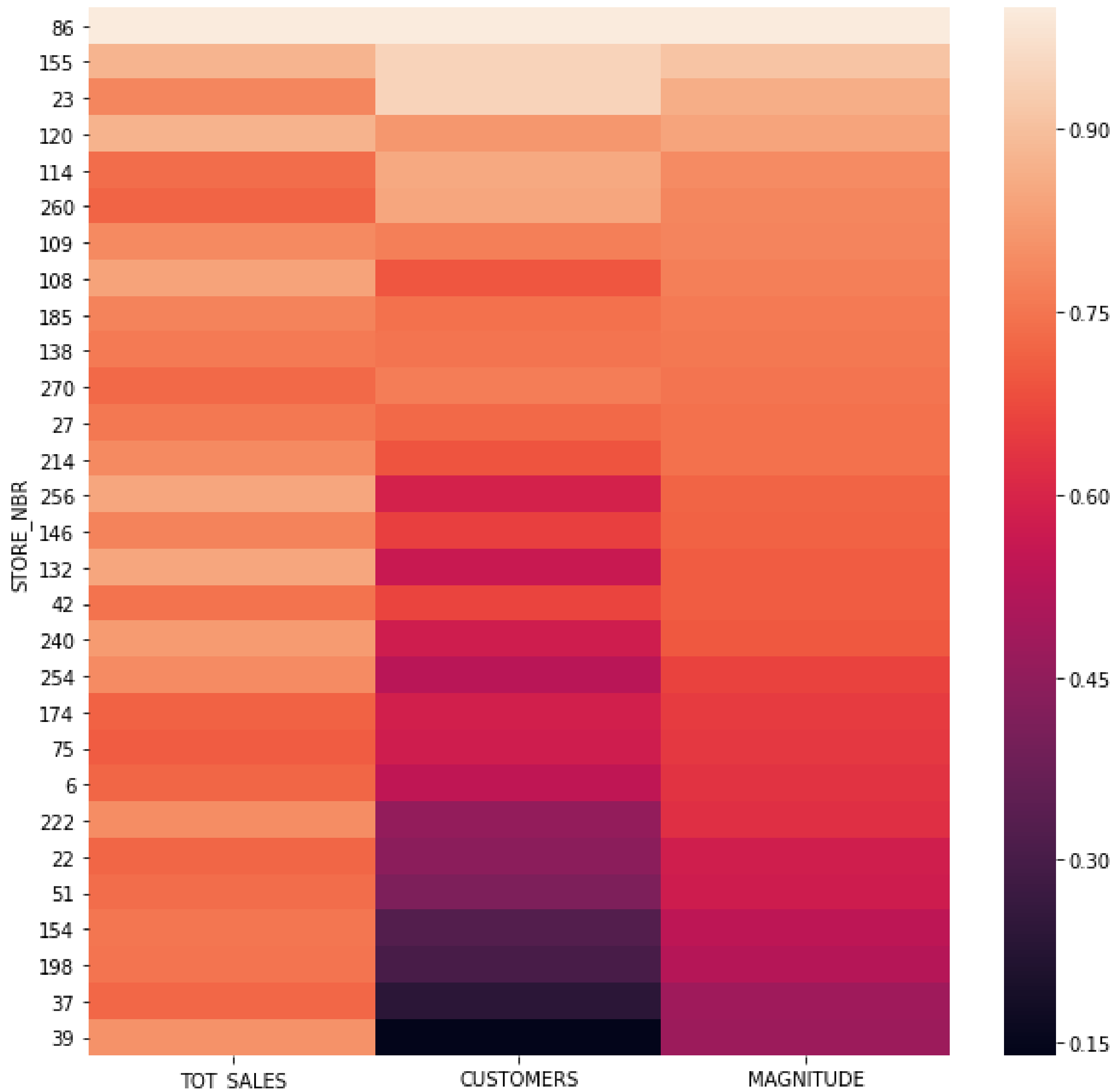
```python
#Taking 0.7 as threshold corelation
corr86[(corr86.MAGNITUDE.abs()>0.7)].plot(kind='bar',figsize=(15,8))
```

```
<AxesSubplot:xlabel='STORE_NBR'>
```



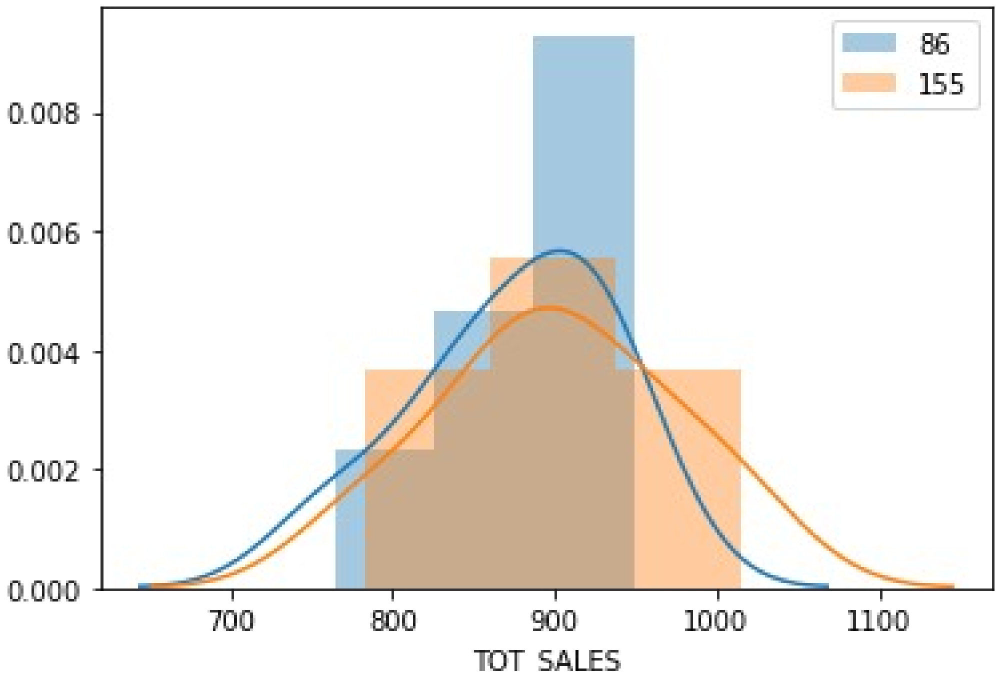

```python
plt.figure(figsize=(10,10))
sns.heatmap(corr86[corr86.TOT_SALES.abs()>0.7])
```

```
<AxesSubplot:ylabel='STORE_NBR'>
```

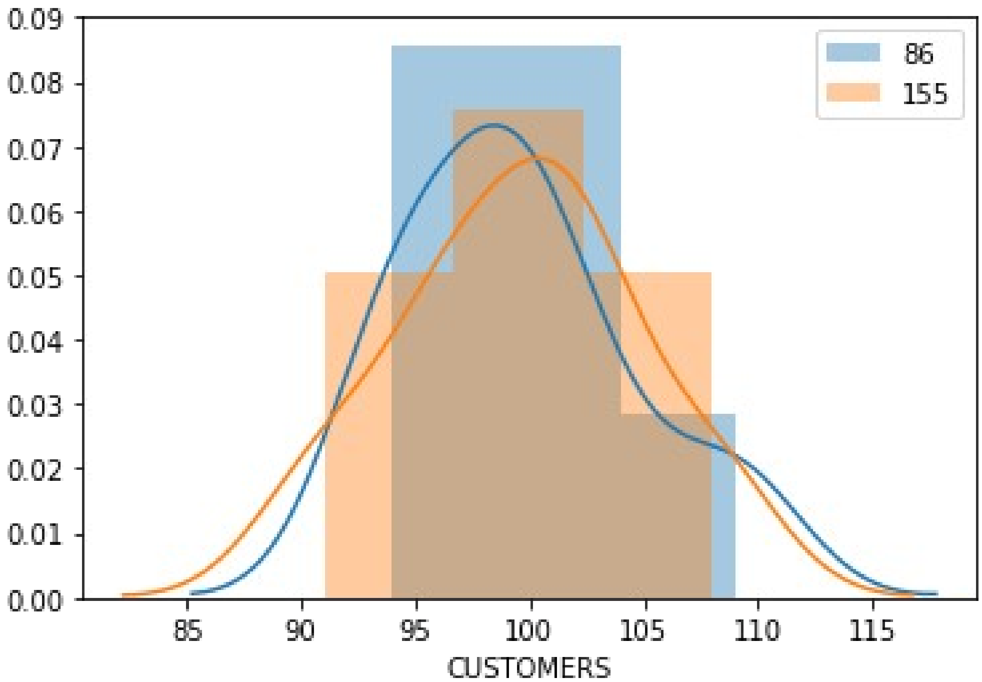


Taking the store 155 into consideration plotting different measure against those of store 86

```
sns.distplot(metrics.loc[86]['TOT_SALES'])
sns.distplot(metrics.loc[155]['TOT_SALES'])
plt.legend(labels=['86','155'])

<matplotlib.legend.Legend at 0x27654e85c48>
```

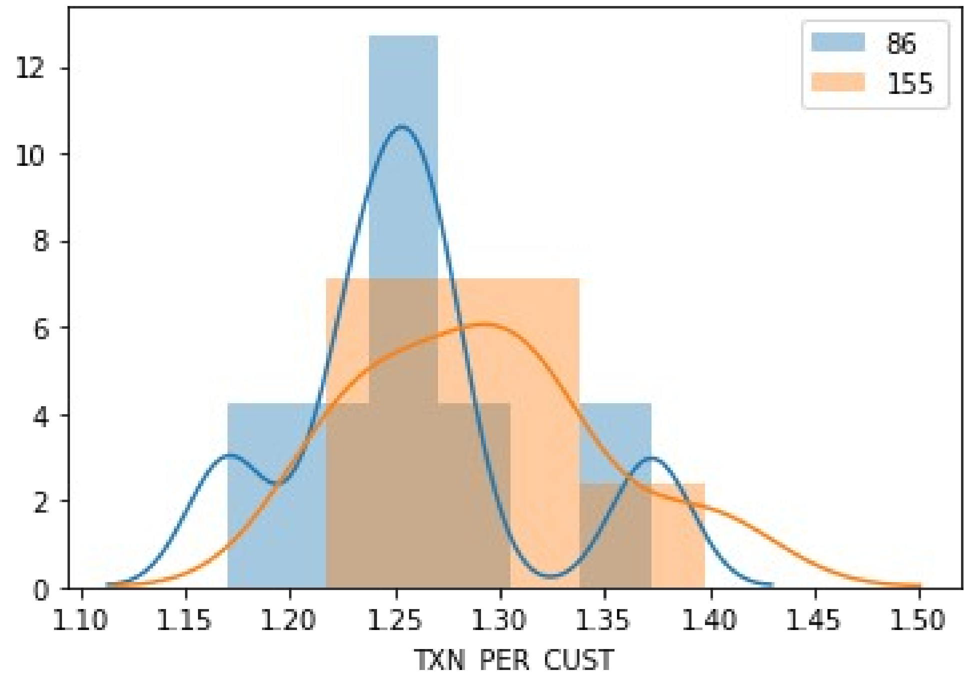



```
sns.distplot(metrics.loc[86]['CUSTOMERS'])
sns.distplot(metrics.loc[155]['CUSTOMERS'])
plt.legend(labels=['86','155'])

<matplotlib.legend.Legend at 0x276569f5b48>
```



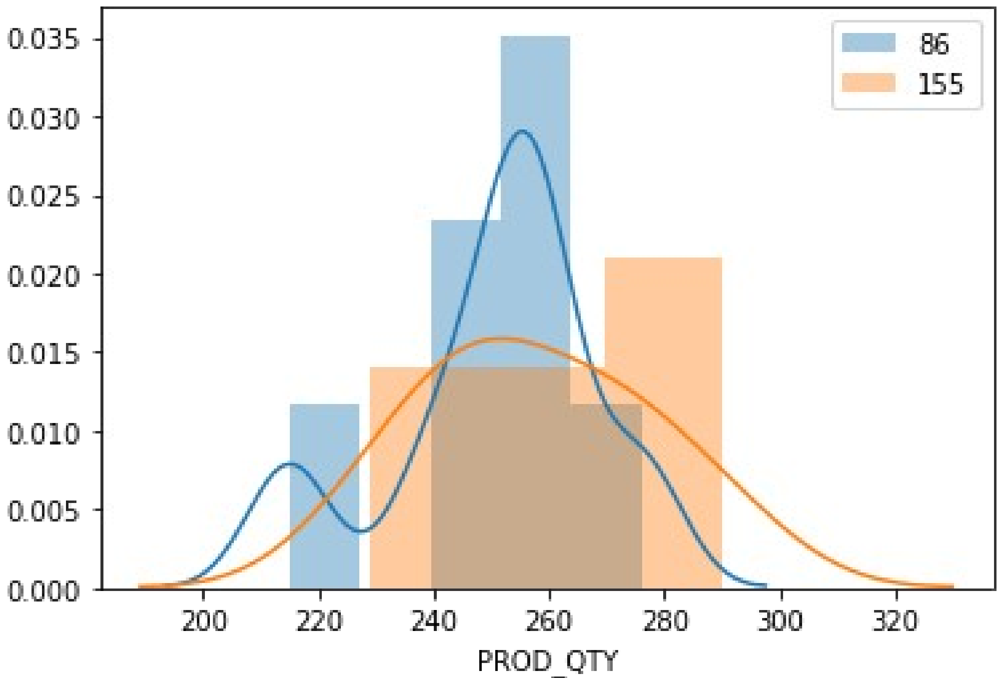
```
sns.distplot(metrics.loc[86]['TXN_PER_CUST'])
sns.distplot(metrics.loc[155]['TXN_PER_CUST'])
plt.legend(labels=['86','155'])
```

```
<matplotlib.legend.Legend at 0x276569f5988>
```




```
sns.distplot(metrics.loc[86]['PROD_QTY'])
sns.distplot(metrics.loc[155]['PROD_QTY'])
plt.legend(labels=['86','155'])
```

```
<matplotlib.legend.Legend at 0x27651d82f08>
```



Since distributions of store 155 are similar to that of store 86, selecting store 155 as control store with max similarities to store 86

Calculating difference between scaled control sales and trial sales

Let null hypothesis be that both stores 77 ans 233 have no difference

```
from scipy.stats import ks_2samp,ttest_ind,ttest_rel,t

# difference between control and trial sales
a=[]
for x in metrics.columns:
    a.append(ks_2samp(metrics.loc[86][x], metrics.loc[155][x]))
a=pd.DataFrame(a,index=metrics.columns)

a
```

	statistic	pvalue
TOT_SALES	0.285714	0.962704
CUSTOMERS	0.285714	0.962704
PROD_QTY	0.285714	0.962704
PRICE_PER_UNIT	0.428571	0.575175
CHIP_PER_TXN	0.428571	0.575175
TXN_PER_CUST	0.428571	0.575175

For pre trial period, since p-values for TOT_SALES, CUSTOMERS and PROD_QTY are high (say more than 0.95), we can't reject the null hypothesis

Assessment of trial

The trial period goes from the start of February 2019 to April 2019. We now want to see if there has been an uplift in overall chip sales.

```
b=[]
for x in trial.columns:
    b.append(ttest_ind(trial.loc[86][x].tail(2), trial.loc[155]
[x].tail(2)))
b=pd.DataFrame(b,index=metrics.columns)

b
```

	statistic	pvalue
TOT_SALES	1.234512	0.342378
CUSTOMERS	2.414953	0.137076
PROD_QTY	1.862532	0.203568
PRICE_PER_UNIT	0.366214	0.749316
CHIP_PER_TXN	-0.285938	0.801822
TXN_PER_CUST	-1.074767	0.394929

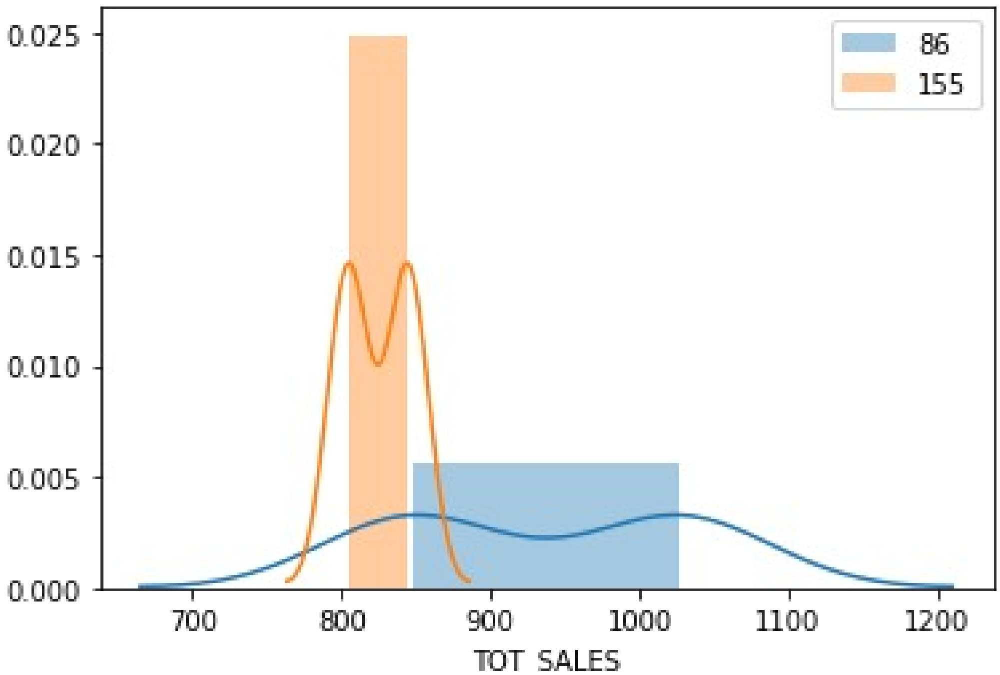
```
#critical value
t.ppf(0.95,df=7)

1.894578605061305
```

Since all of the p-values are high (say more than 0.05), we reject the null hypothesis i.e. there means are significantly different. We can observe that the t-value is much larger than the 95th percentile value of the t-distribution for March and April - i.e. the increase in sales in the trial store in March and April is statistically greater than in the control store.

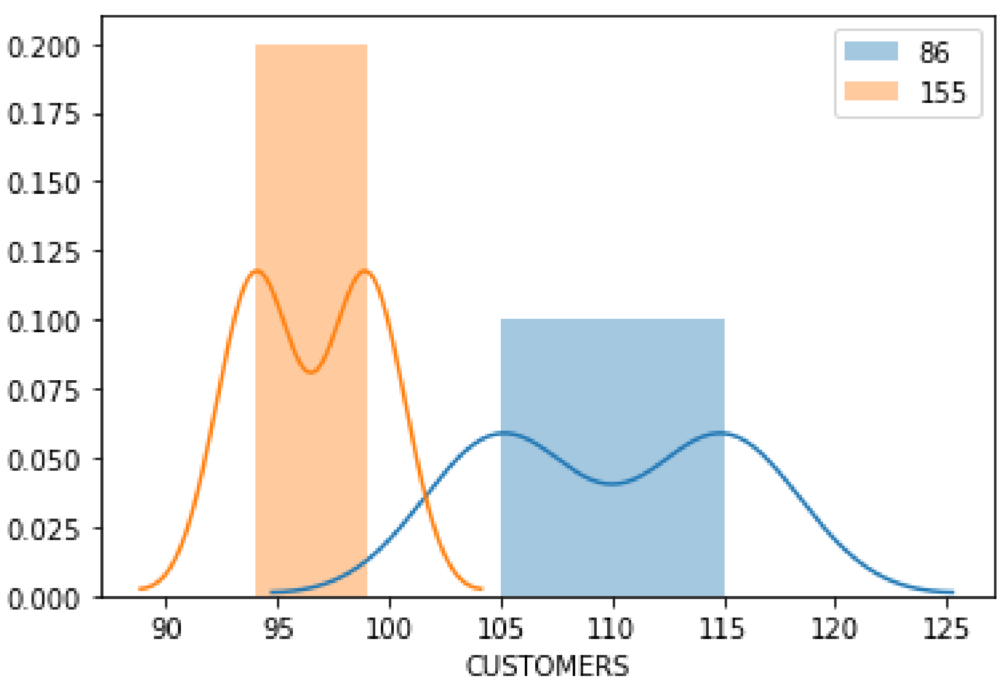
The results show that the trial in store 88 is significantly different to its control store in the trial period as the trial store performance lies outside of the 5% to 95% confidence interval of the control store in two of the three trial months.

Vizualizing means

```
sns.distplot(trial.loc[86]['TOT_SALES'].tail(2))
sns.distplot(trial.loc[155]['TOT_SALES'].tail(2))
plt.legend(labels=['86','155'])

<matplotlib.legend.Legend at 0x27651e6f608>
```




```
sns.distplot(trial.loc[86]['CUSTOMERS'].tail(2))
sns.distplot(trial.loc[155]['CUSTOMERS'].tail(2))
plt.legend(labels=['86','155'])

<matplotlib.legend.Legend at 0x2765323f388>
```



It can be visualized that the is a significant difference in the means, so trial store behavior(86) is different from control store (155).

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 increasingthe 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.

Store 88

Finding stores corelated to store 88

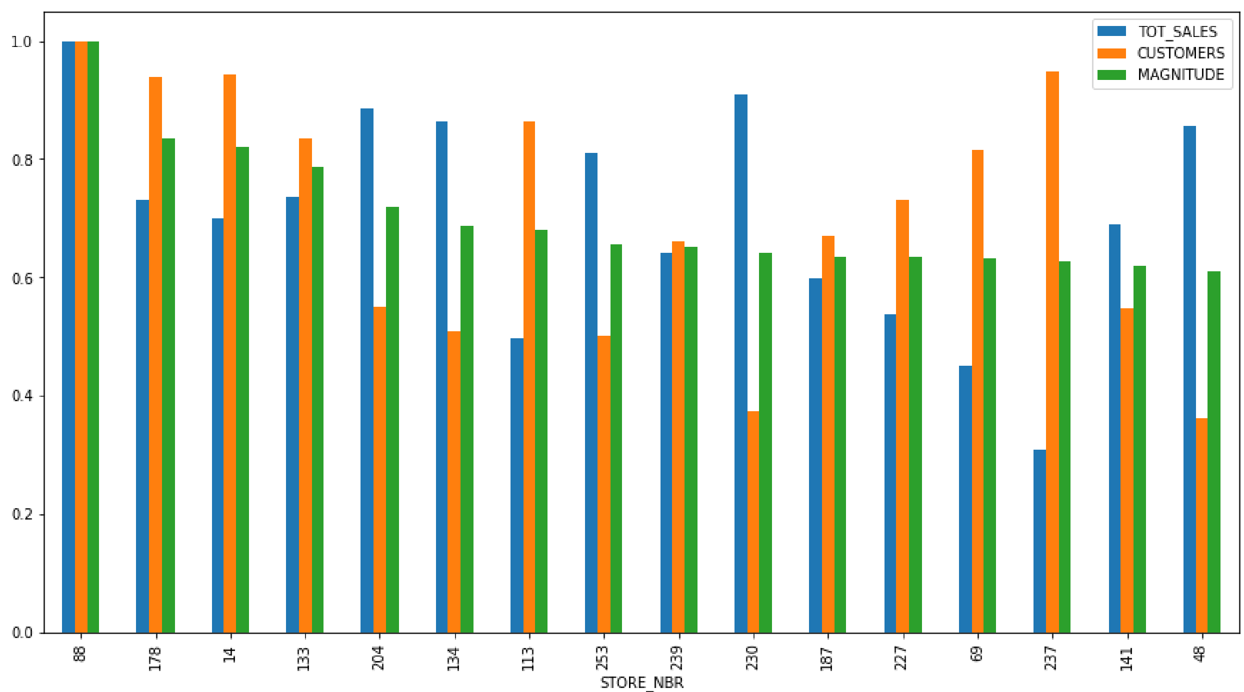
```
corr88=calcCorr(88)

corr88.head(3)

           TOT_SALES  CUSTOMERS
STORE_NBR
1           0.813636   0.305334
2          -0.067927  -0.452379
3          -0.507847   0.522884

corr88=standardizer(corr88)
corr88

           TOT_SALES  CUSTOMERS  MAGNITUDE
STORE_NBR
1           0.813636   0.305334   0.559485
2           0.067927   0.452379   0.260153
3           0.507847   0.522884   0.515365
4           0.745566   0.361503   0.553534
5           0.190330   0.025320   0.107825
...              ...        ...        ...
268         0.021429   0.672672   0.347050
269         0.172578   0.274781   0.223679
270         0.723272   0.103032   0.413152
271         0.103037   0.018831   0.060934
272         0.772772   0.026909   0.399841

[266 rows x 3 columns]

corr88=corr88.sort_values(['MAGNITUDE'],ascending=False).dropna()

corr88.head(15)

           TOT_SALES  CUSTOMERS  MAGNITUDE
STORE_NBR
88          1.000000   1.000000   1.000000
```

```
178          0.731857   0.939466   0.835661
14           0.698557   0.942976   0.820767
133          0.735407   0.835426   0.785417
204          0.885774   0.550263   0.718018
134          0.864293   0.508880   0.686587
113          0.495763   0.862632   0.679198
253          0.811838   0.500962   0.656400
239          0.642329   0.660672   0.651501
230          0.908883   0.373350   0.641117
187          0.599076   0.671264   0.635170
227          0.537448   0.729943   0.633695
69           0.450029   0.815792   0.632910
237          0.308479   0.947326   0.627903
141          0.690590   0.547399   0.618994
```

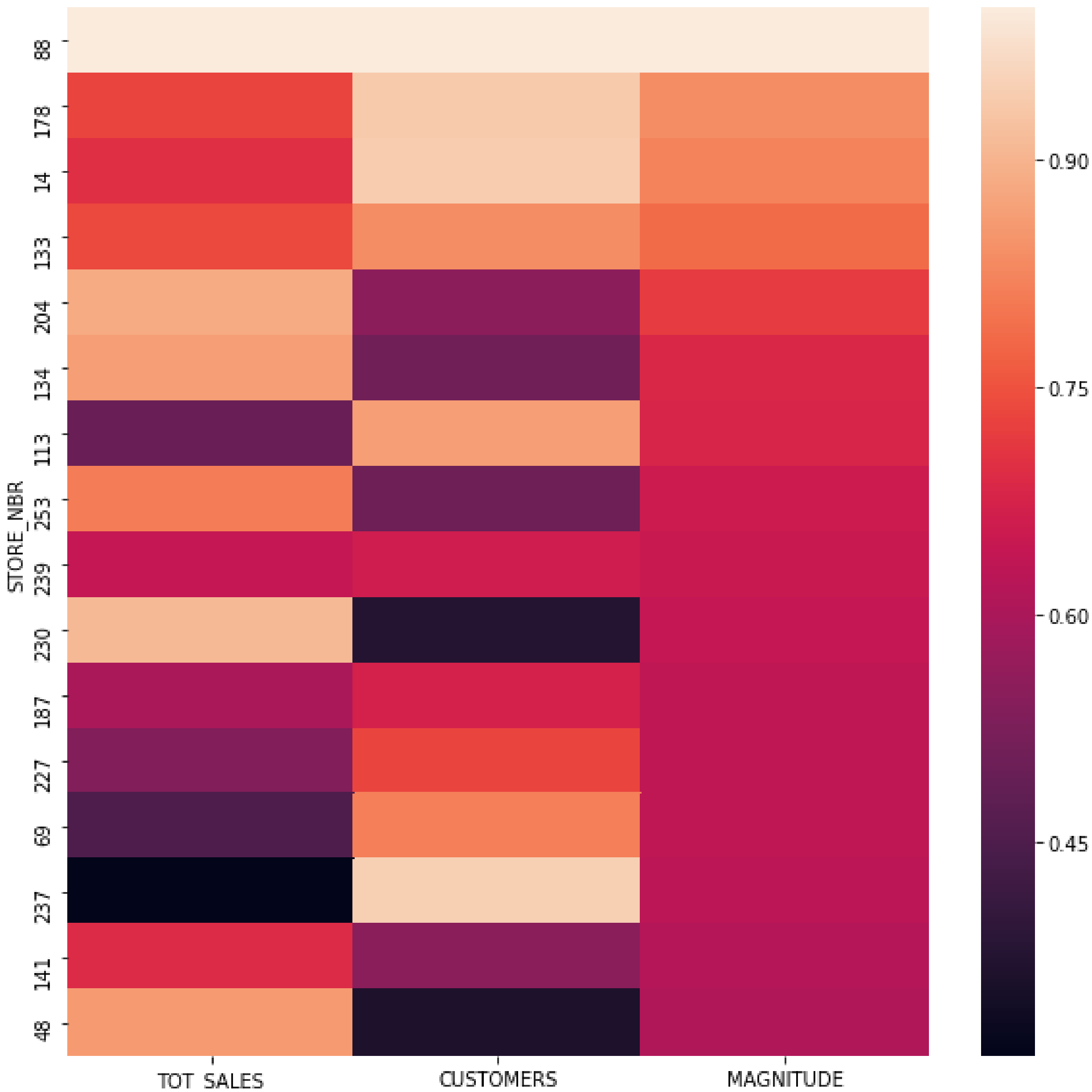
**shows that stores 178,14,133 are the most correlated to store 88

Visualizing ...

```
#Taking 0.6 as threshold corelation
corr88[(corr88.MAGNITUDE.abs()>0.6)].plot(kind='bar',figsize=(15,8))

<AxesSubplot:xlabel='STORE_NBR'>
```

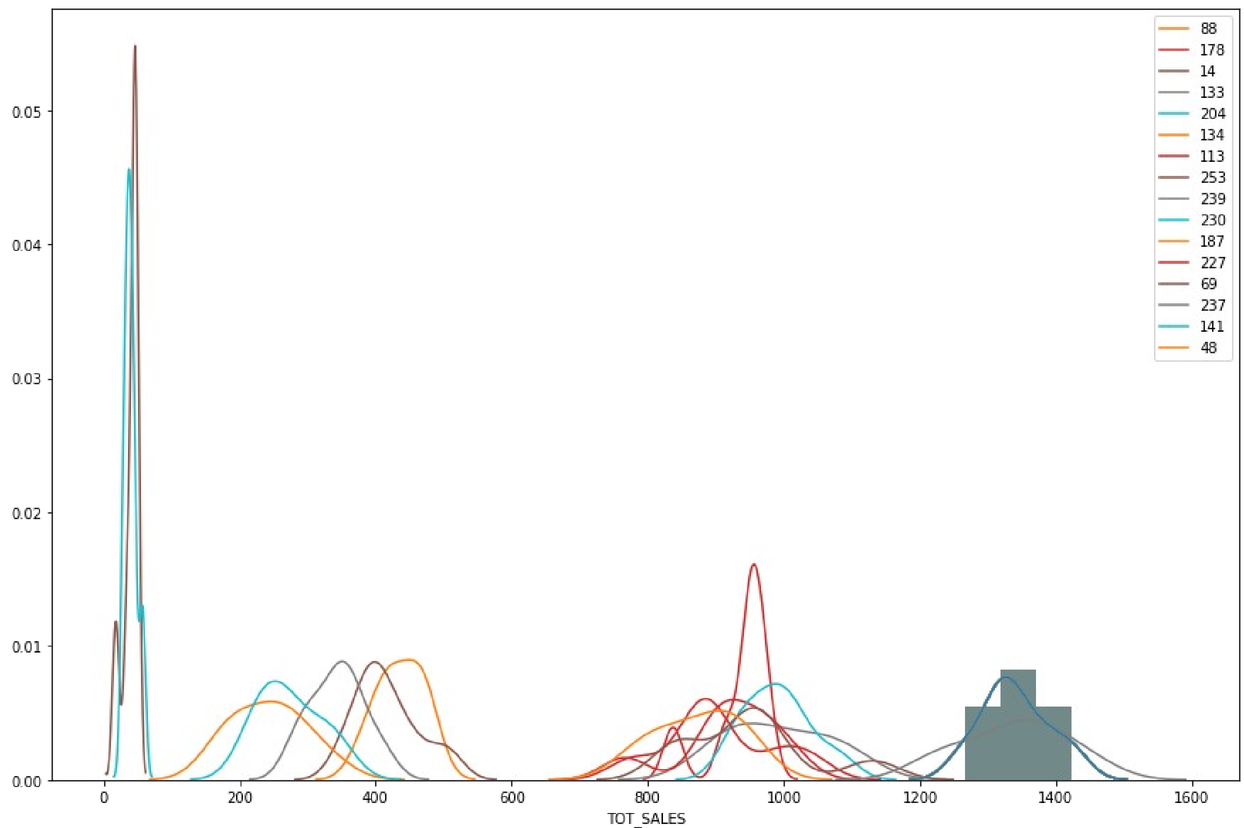



```
plt.figure(figsize=(10,10))
sns.heatmap(corr88[corr88.MAGNITUDE.abs()>0.6])

<AxesSubplot:ylabel='STORE_NBR'>
```




```
plt.figure(figsize=(15,10))
for x in corr88[corr88.MAGNITUDE.abs()>0.6].index:
    sns.distplot(metrics.loc[88]['TOT_SALES'])
    sns.distplot(metrics.loc[x]['TOT_SALES'],label=x,hist=False)
plt.legend()
```

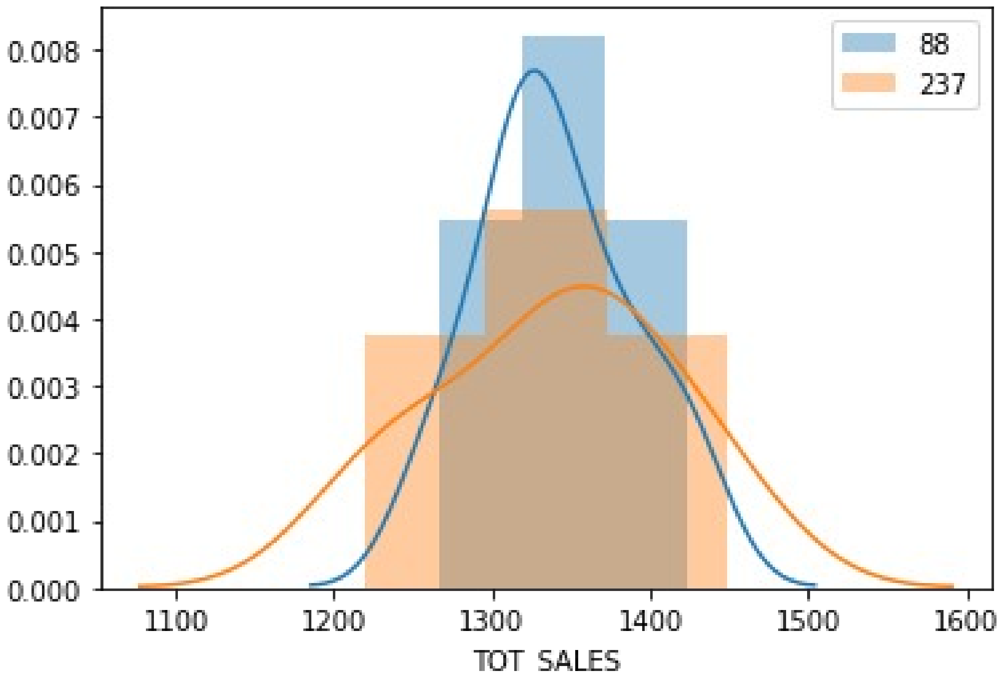
```
<matplotlib.legend.Legend at 0x27656560948>
```



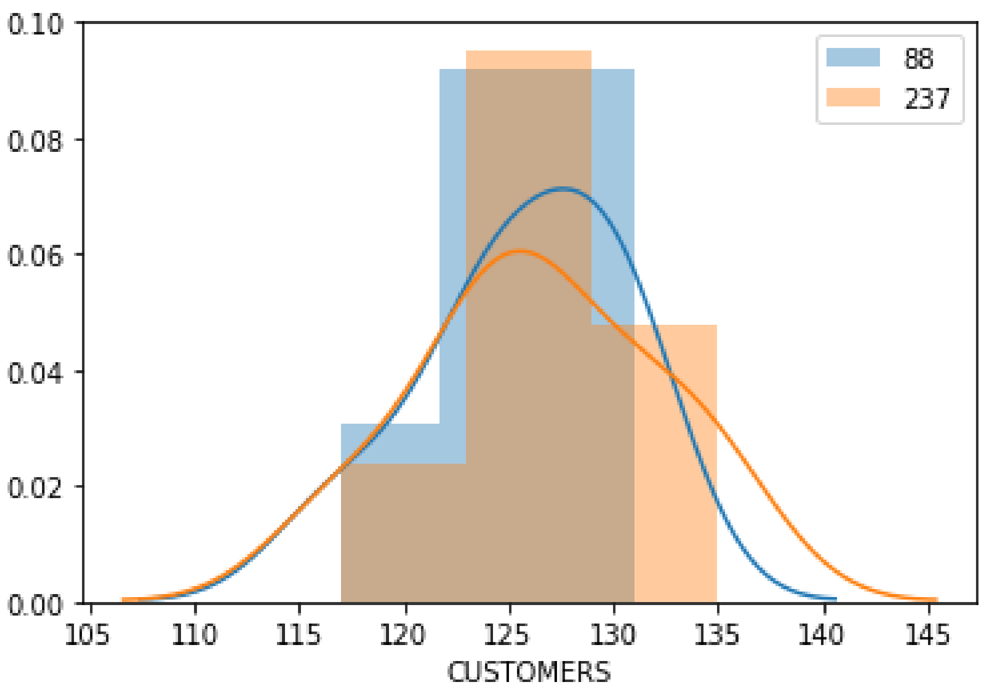
Therefore Taking the store 237 into consideration plotting different measure against those of store 88

```
sns.distplot(metrics.loc[88]['TOT_SALES'])
sns.distplot(metrics.loc[237]['TOT_SALES'])
plt.legend(labels=['88','237'])
```

```
<matplotlib.legend.Legend at 0x27654b91488>
```

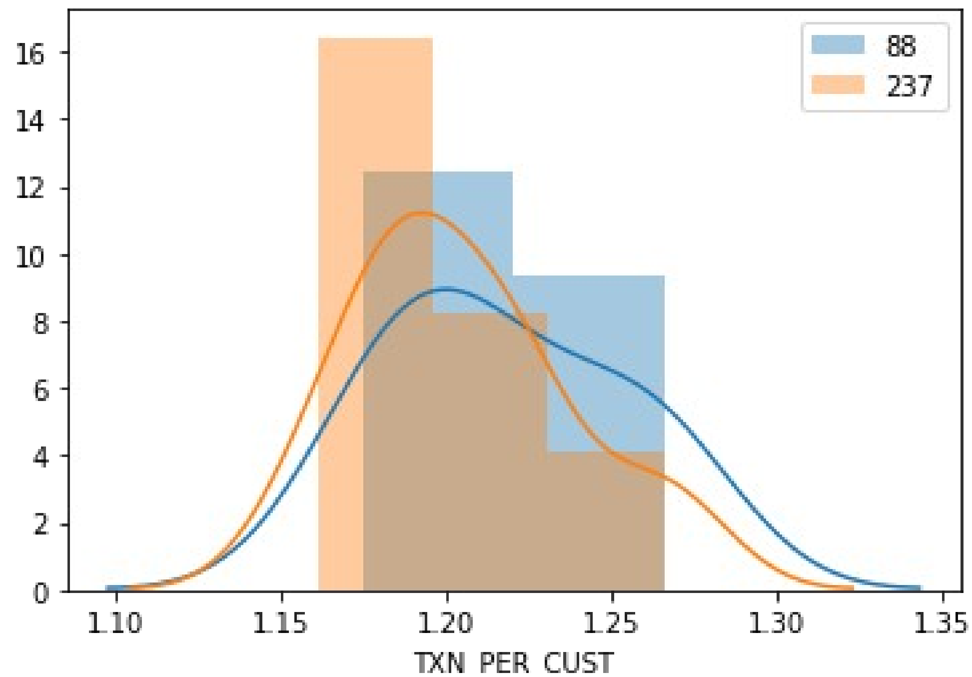



```
sns.distplot(metrics.loc[88]['CUSTOMERS'])
sns.distplot(metrics.loc[237]['CUSTOMERS'])
plt.legend(labels=['88','237'])

<matplotlib.legend.Legend at 0x2765703b108>
```



```
sns.distplot(metrics.loc[88]['TXN_PER_CUST'])
sns.distplot(metrics.loc[237]['TXN_PER_CUST'])
plt.legend(labels=['88','237'])
```

```
<matplotlib.legend.Legend at 0x276543dfd48>
```



Since distributions of store 237 are similar to that of store 88, selecting store 237 as control store with max similarities to store 88

Calculating difference between scaled control sales and trial sales

Let null hypothesis be that both stores 88 ans 237 have no difference

```
from scipy.stats import ks_2samp,ttest_ind,t

# difference between control and trial sales
a=[]
for x in metrics.columns:
    a.append(ks_2samp(metrics.loc[88][x], metrics.loc[237][x]))
a=pd.DataFrame(a,index=metrics.columns)

a
```

	statistic	pvalue
TOT_SALES	0.285714	0.962704
CUSTOMERS	0.285714	0.962704

```
PROD_QTY          0.285714  0.962704
PRICE_PER_UNIT    0.428571  0.575175
CHIP_PER_TXN      0.571429  0.212121
TXN_PER_CUST      0.285714  0.962704
```

For pre trial period, since all of the p-values are high (say more than 0.05), we can't reject the null hypothesis

Assessment of trial

The trial period goes from the start of February 2019 to April 2019. We now want to see if there has been an uplift in overall chip sales.

Sampling march and april from the 3 months

```
b=[]
for x in trial.columns:
    b.append(ttest_ind(trial.loc[86][x].tail(2), trial.loc[237]
[x].tail(2)))
b=pd.DataFrame(b,index=metrics.columns)

b
```

	statistic	pvalue
TOT_SALES	-3.010587	0.094888
CUSTOMERS	-1.890571	0.199245
PROD_QTY	-0.266076	0.815100
PRICE_PER_UNIT	-6.804115	0.020925
CHIP_PER_TXN	-0.465456	0.687370
TXN_PER_CUST	9.547202	0.010794

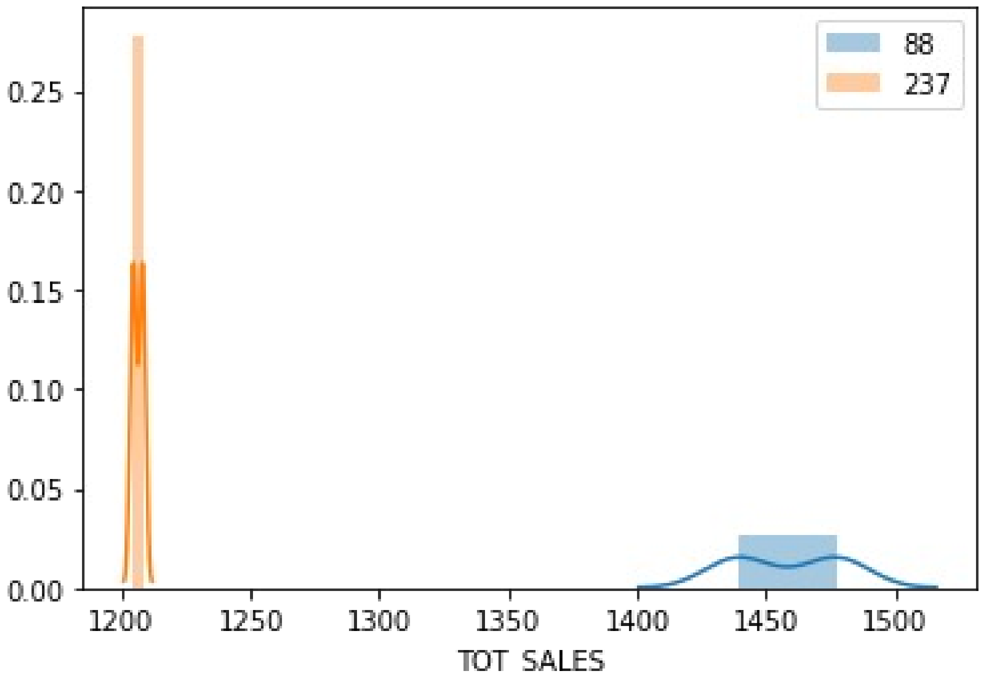
```
#critical value
t.ppf(0.95,df=7)

1.894578605061305
```

Since all of the p-values are high (say more than 0.05), we reject the null hypothesis i.e. there means are significantly different.

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.

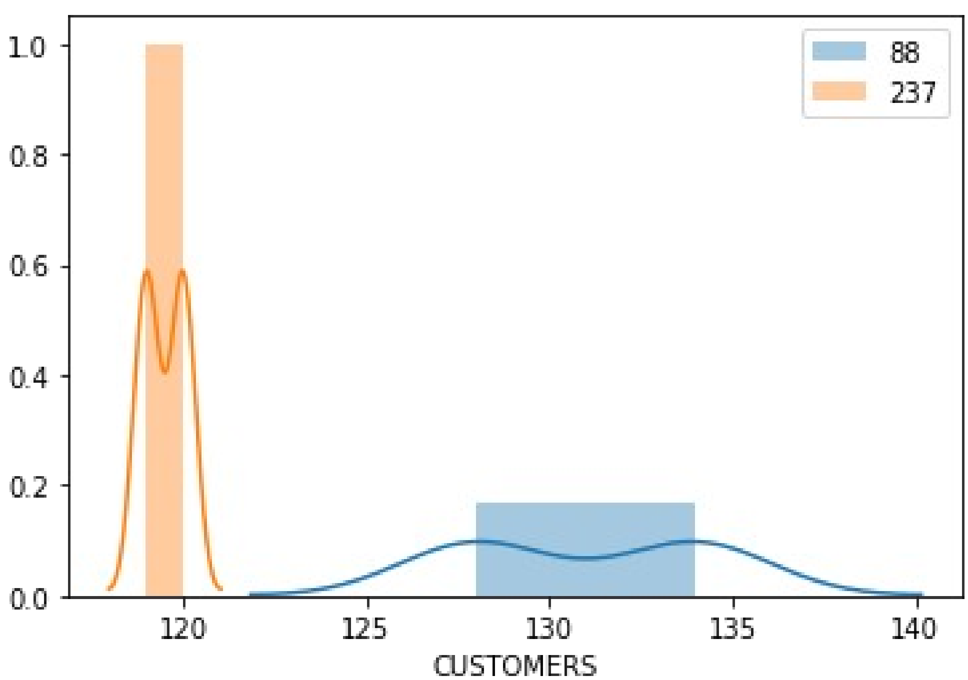
Vizualizing means

```
sns.distplot(trial.loc[88]['TOT_SALES'].tail(2))
sns.distplot(trial.loc[237]['TOT_SALES'].tail(2))
plt.legend(labels=['88','237'])

<matplotlib.legend.Legend at 0x27653e0d288>
```




```
sns.distplot(trial.loc[88]['CUSTOMERS'].tail(2))
sns.distplot(trial.loc[237]['CUSTOMERS'].tail(2))
plt.legend(labels=['88','237'])
```

```
<matplotlib.legend.Legend at 0x276534824c8>
```

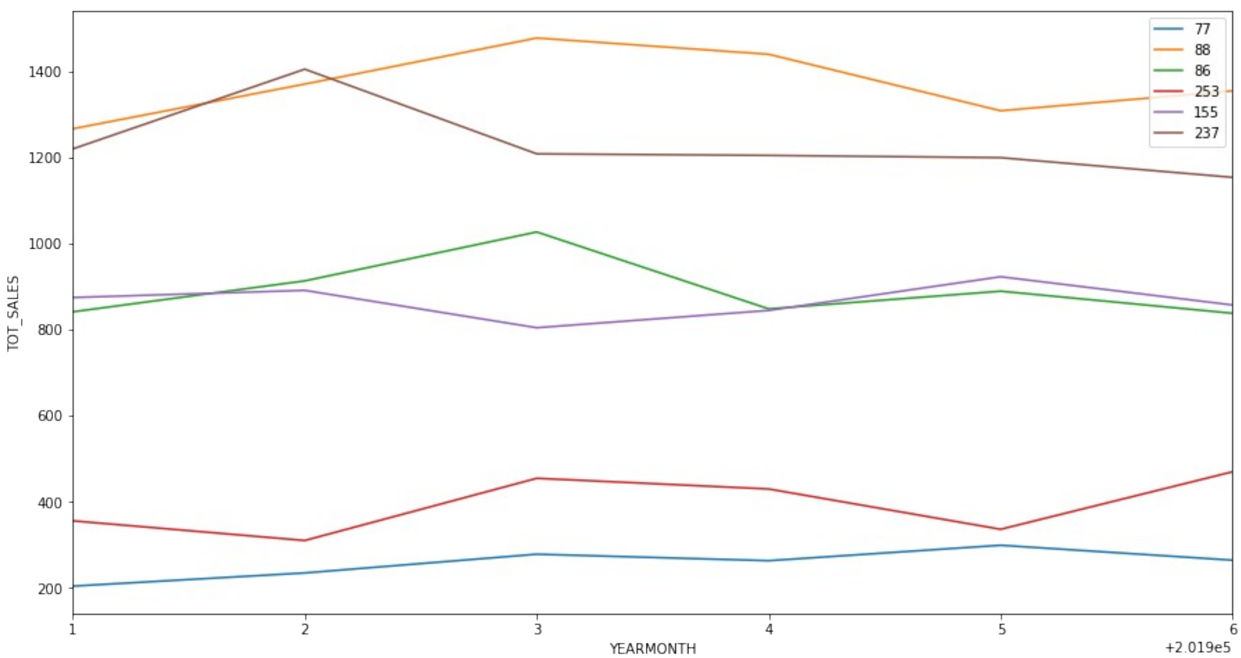


It can be visualized that the is a significant difference in the means, so trial store behavior(88) is different from control store (237).

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.

```
fig, ax = plt.subplots(figsize=(15, 8))
x=['77','88','86','253','155','237']
for i in  x:

sns.lineplot(data=full.loc[int(i)],y='TOT_SALES',x=full.index.get_leve
l_values(1).unique(),label=i)


#ax.set_xlim(201807,201812)
ax.set_xlim(201901,201906)
```

```
(201901.0, 201906.0)
```



Conclusion

The results for trial stores 77 and 88 during the trial period show a significant difference in at least two of the three trial months but this is not the case for trial store 86. We can check with the client if the implementation of the trial was different in trial store 86 but overall, the trial shows a significant increase in sales.