Quantium Data Analysis Intenrship_Task 2

December 26, 2023

[2]:
```python
# import statements
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import datetime as dt
import seaborn as sns

chips_final = pd.read_csv('chips_final.csv')
```

[3]:
```python
chips_final
```

[3]:
```
        Unnamed: 0  SHORT_DATE  STORE_NBR  LYLTY_CARD_NBR    TXN_ID  \
0                0  2018-10-17        1.0          1000.0       1.0
1                1  2019-05-14        1.0          1307.0     348.0
2                2  2019-05-20        1.0          1343.0     383.0
3                3  2018-08-17        2.0          2373.0     974.0
4                4  2018-08-18        2.0          2426.0    1038.0
…              …           …          …               …         …
264830      264830  2018-08-13      272.0        272358.0  270154.0
264831      264831  2018-11-06      272.0        272379.0  270187.0
264832      264832  2018-12-27      272.0        272379.0  270188.0
264833      264833  2018-09-22      272.0        272380.0  270189.0
264834      264834  2018-12-25        NaN             NaN       NaN

                    LIFESTAGE PREMIUM_CUSTOMER  PROD_NBR  \
0       YOUNG SINGLES/COUPLES          Premium       5.0
1      MIDAGE SINGLES/COUPLES           Budget      66.0
2      MIDAGE SINGLES/COUPLES           Budget      61.0
3      MIDAGE SINGLES/COUPLES           Budget      69.0
4      MIDAGE SINGLES/COUPLES           Budget     108.0
…                           …              …         …
264830  YOUNG SINGLES/COUPLES          Premium      74.0
264831  YOUNG SINGLES/COUPLES          Premium      51.0
264832  YOUNG SINGLES/COUPLES          Premium      42.0
264833  YOUNG SINGLES/COUPLES          Premium      74.0
264834                    NaN              NaN       NaN

                                  PROD_NAME     BRAND WEIGHT  PROD_QTY  \
```

```
0         Natural Chip        Compny SeaSalt175g   Natural   175g       2.0
1                      CCs Nacho Cheese     175g       CCs   175g       3.0
2         Smiths Crinkle Cut  Chips Chicken 170g    Smiths   170g       2.0
3         Smiths Chip Thinly  S/Cream&Onion 175g    Smiths   175g       5.0
4       Kettle Tortilla ChpsHny&Jlpno Chili 150g    Kettle   150g       3.0
…                                          …        …    …        …
264830             Tostitos Splash Of  Lime 175g  Tostitos   175g       1.0
264831                 Doritos Mexicana     170g   Doritos   170g       2.0
264832   Doritos Corn Chip Mexican Jalapeno 150g   Doritos   150g       2.0
264833             Tostitos Splash Of  Lime 175g  Tostitos   175g       2.0
264834                                       NaN       NaN    NaN       NaN

        TOT_SALES BAG_SIZE
0             6.0    Small
1             6.3    Small
2             2.9    Small
3            15.0    Small
4            13.8    Small
…           …      …
264830        4.4    Small
264831        8.8    Small
264832        7.8    Small
264833        8.8    Small
264834        NaN      NaN

[264835 rows x 14 columns]
```

[5]:
```
# remove old index
chips_final = chips_final.drop('Unnamed: 0', axis=1)
```

[6]:
```
chips_final.to_csv('chips_final.csv')
```

[7]:
```
chips_final['SHORT_DATE'].dtype
```

[7]:
```
dtype('O')
```

[8]:
```
# lets create a month and year column
chips_final['SHORT_DATE'] = pd.to_datetime(chips_final['SHORT_DATE'])

chips_final['MONTH_YEAR'] = chips_final['SHORT_DATE'].dt.strftime('%m/%Y')
```

[9]:
```
chips_final['MONTH_YEAR']
```

[9]:
```
0         10/2018
1         05/2019
2         05/2019
3         08/2018
```

```
4         08/2018
           …
264830    08/2018
264831    11/2018
264832    12/2018
264833    09/2018
264834    12/2018
Name: MONTH_YEAR, Length: 264835, dtype: object
```

[10]:
```
# to find comparable stores, we will isolate the timframe from July 2018 to␣
↪January 31st 2019

chips_final['MONTH_YEAR'] = pd.to_datetime(chips_final['MONTH_YEAR'])
chips_before = chips_final[(chips_final['MONTH_YEAR'] >= '07/2018') &␣
↪(chips_final['MONTH_YEAR'] <= '01/2019')]

chips_before['MONTH_YEAR'].value_counts()
```

[10]:
```
2018-12-01    22836
2018-07-01    22562
2018-08-01    22410
2018-10-01    22288
2019-01-01    22161
2018-11-01    21852
2018-09-01    21743
Name: MONTH_YEAR, dtype: int64
```

[16]:
```
# grouping by store number and month year
chips_grp_before = chips_before.groupby(['STORE_NBR', 'MONTH_YEAR'])

total_grp = chips_grp_before['TOT_SALES'].sum()

total_grp
```

[16]:
```
STORE_NBR  MONTH_YEAR
1.0        2018-07-01    206.9
           2018-08-01    176.1
           2018-09-01    278.8
           2018-10-01    188.1
           2018-11-01    192.6
                          …
272.0      2018-09-01    304.7
           2018-10-01    430.6
           2018-11-01    376.2
           2018-12-01    403.9
           2019-01-01    423.0
Name: TOT_SALES, Length: 1848, dtype: float64
```

```
[18]: # looking at total sales by store number
chips_grp_sales = chips_before.groupby('STORE_NBR')
total_sales = chips_grp_sales['TOT_SALES'].sum()
total_sales
```

```
[18]: STORE_NBR
1.0      1386.90
2.0      1128.50
3.0      7526.15
4.0      9127.00
5.0      5739.70
           …
268.0    1549.05
269.0    6664.50
270.0    6697.95
271.0    5765.10
272.0    2744.35
Name: TOT_SALES, Length: 271, dtype: float64
```

```
[19]: # looking for trail store
trial_store = total_sales[77:88]
trial_store
```

```
[19]: STORE_NBR
77.0    1699.00
78.0    5466.40
79.0    7143.15
80.0    6953.40
81.0    8260.30
82.0    2289.90
83.0    5739.80
84.0    3238.50
85.0      13.90
86.0    6119.85
87.0    2385.50
88.0    9383.60
Name: TOT_SALES, dtype: float64
```

Total sales for trial stores between July 2018 and January 2019

- Store 77: 1699.00
- Store 86: 6119.85
- Store 88: 9383.60

Now since we have the total sales for the trial stores, lets look for matching control stores for each.

```
[20]: # sorting stores by total sales looking for a match for store 77
total_sorted = total_sales.sort_values(ascending=True)
```

```
total_sorted.iloc[63:73]
```

[20]:
```
STORE_NBR
53.0     1611.1
6.0      1618.8
255.0    1636.6
233.0    1659.8
188.0    1683.5
77.0     1699.0
187.0    1702.2
90.0     1736.4
46.0     1758.0
220.0    1788.6
Name: TOT_SALES, dtype: float64
```

[21]:
```
# isolating the 10 stores
stores_control_1 = [6,46,53,77,90,187,188,220,233,255]
control_1 = pd.DataFrame({'Value': total_grp[stores_control_1]})
print(control_1)
```

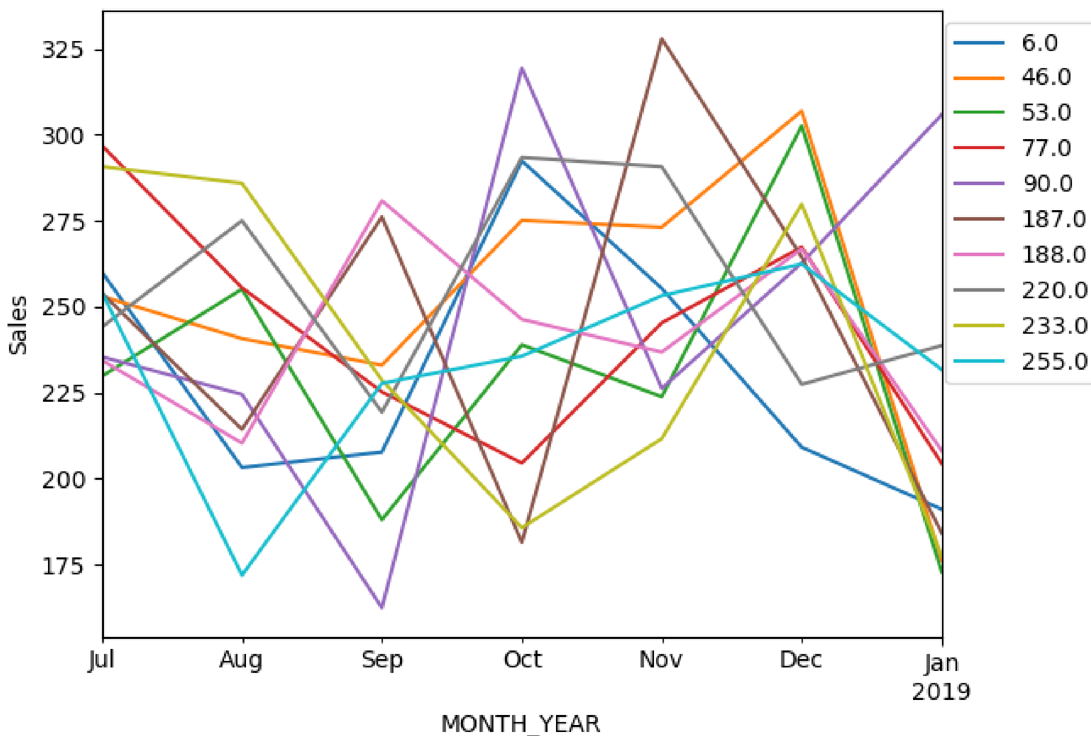
```
                      Value
STORE_NBR MONTH_YEAR
6.0       2018-07-01  260.0
          2018-08-01  203.2
          2018-09-01  207.7
          2018-10-01  292.4
          2018-11-01  255.3
…                     …
255.0     2018-09-01  227.7
          2018-10-01  235.6
          2018-11-01  253.2
          2018-12-01  262.4
          2019-01-01  231.7

[70 rows x 1 columns]
```

[22]:
```
# putting the 10 stores in a pivot chart format
pivot_chips_1 = control_1.pivot_table(index='MONTH_YEAR', columns='STORE_NBR',␣
 ↪values='Value')
pivot_chips_1
```

[22]:
```
STORE_NBR   6.0    46.0   53.0   77.0   90.0   187.0  188.0  220.0  233.0  \
MONTH_YEAR
2018-07-01  260.0  253.0  229.8  296.8  235.4  253.9  234.4  244.1  290.7
2018-08-01  203.2  240.7  255.1  255.5  224.5  214.3  210.3  275.0  285.9
2018-09-01  207.7  233.0  188.0  225.2  162.4  276.1  280.8  219.3  228.6
2018-10-01  292.4  275.1  238.9  204.5  319.4  181.4  246.3  293.4  185.7
2018-11-01  255.3  273.1  223.8  245.3  226.2  327.9  236.8  290.7  211.6
```

```
2018-12-01  209.1  306.9  302.6  267.3  262.7  264.4  266.8  227.4  279.8
2019-01-01  191.1  176.2  172.9  204.4  305.8  184.2  208.1  238.7  177.5

STORE_NBR   255.0
MONTH_YEAR
2018-07-01  254.1
2018-08-01  171.9
2018-09-01  227.7
2018-10-01  235.6
2018-11-01  253.2
2018-12-01  262.4
2019-01-01  231.7
```

[24]:
```
pivot_chips_1.plot()
plt.legend(loc='upper right', bbox_to_anchor=(1.20,1))
plt.ylabel('Sales')
plt.show()
```

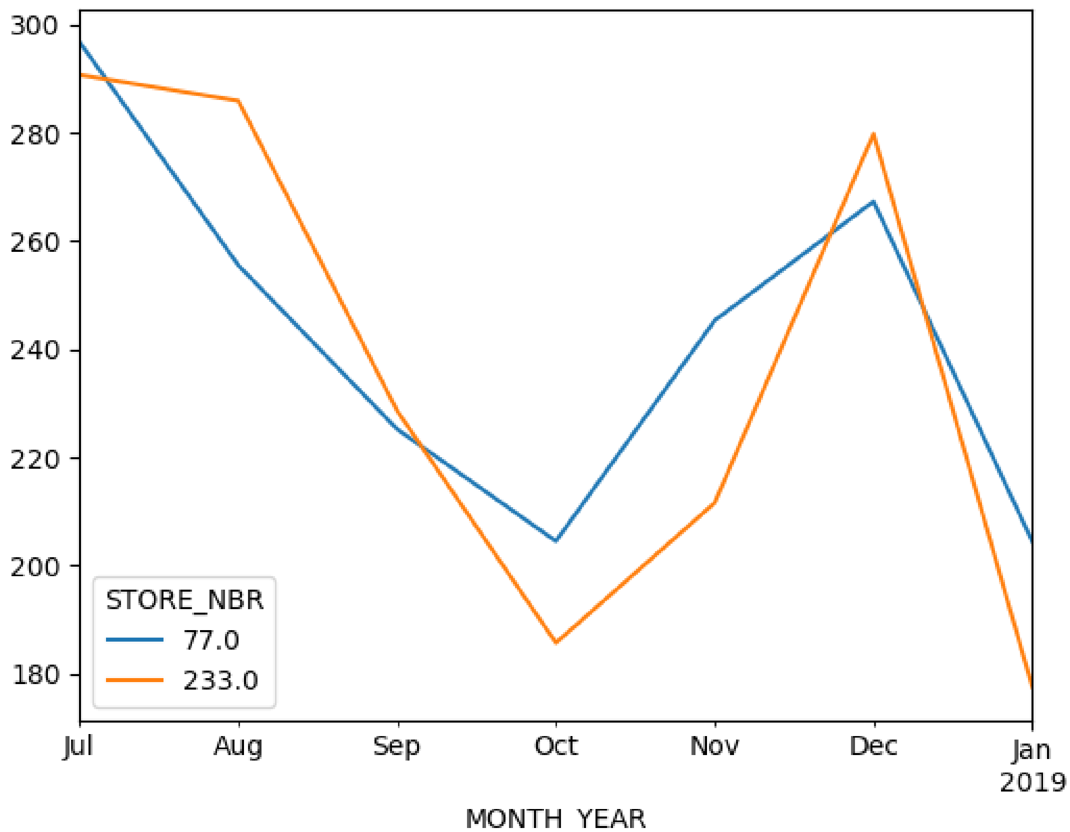


[25]:
```
# looking at correlation
pivot_chips_1.corr(method='pearson')
```

[25]:
```
STORE_NBR      6.0        46.0       53.0       77.0       90.0       187.0   \
STORE_NBR
```

```
6.0         1.000000  0.484580  0.139538  0.042490  0.288923  0.041493
46.0        0.484580  1.000000  0.838008  0.435650 -0.038130  0.433520
53.0        0.139538  0.838008  1.000000  0.532764  0.112228  0.125959
77.0        0.042490  0.435650  0.532764  1.000000 -0.377649  0.460669
90.0        0.288923 -0.038130  0.112228 -0.377649  1.000000 -0.681605
187.0       0.041493  0.433520  0.125959  0.460669 -0.681605  1.000000
188.0       0.115455  0.527886  0.199495  0.042708 -0.422287  0.457048
220.0       0.641903  0.239256  0.133959 -0.183091  0.341478 -0.086637
233.0      -0.176677  0.401329  0.625439  0.903774 -0.453268  0.280566
255.0       0.363013  0.402832  0.101587  0.191091  0.177864  0.421864

STORE_NBR      188.0     220.0     233.0     255.0
STORE_NBR
6.0         0.115455  0.641903 -0.176677  0.363013
46.0        0.527886  0.239256  0.401329  0.402832
53.0        0.199495  0.133959  0.625439  0.101587
77.0        0.042708 -0.183091  0.903774  0.191091
90.0       -0.422287  0.341478 -0.453268  0.177864
187.0       0.457048 -0.086637  0.280566  0.421864
188.0       1.000000 -0.422733  0.090490  0.461834
220.0      -0.422733  1.000000 -0.271433 -0.223507
233.0       0.090490 -0.271433  1.000000 -0.128047
255.0       0.461834 -0.223507 -0.128047  1.000000
```

[27]:
```
# store 233 is the strongest correlation at 0.90

chips_1_graph = pivot_chips_1[[77,233]]
chips_1_graph.plot()
plt.show()
```



For trial store number 77, we will use store number 233 for a control store. It's a 0.90 correlation and only 40 dollar difference between the stores

[28]:
```
# looking for control store to match with store 86
total_sorted.iloc[176:186]
```

[28]:
```
STORE_NBR
23.0     6098.90
48.0     6112.30
172.0    6113.40
13.0     6114.70
86.0     6119.85
196.0    6126.30
57.0     6147.40
30.0     6194.60
236.0    6197.40
105.0    6206.20
Name: TOT_SALES, dtype: float64
```

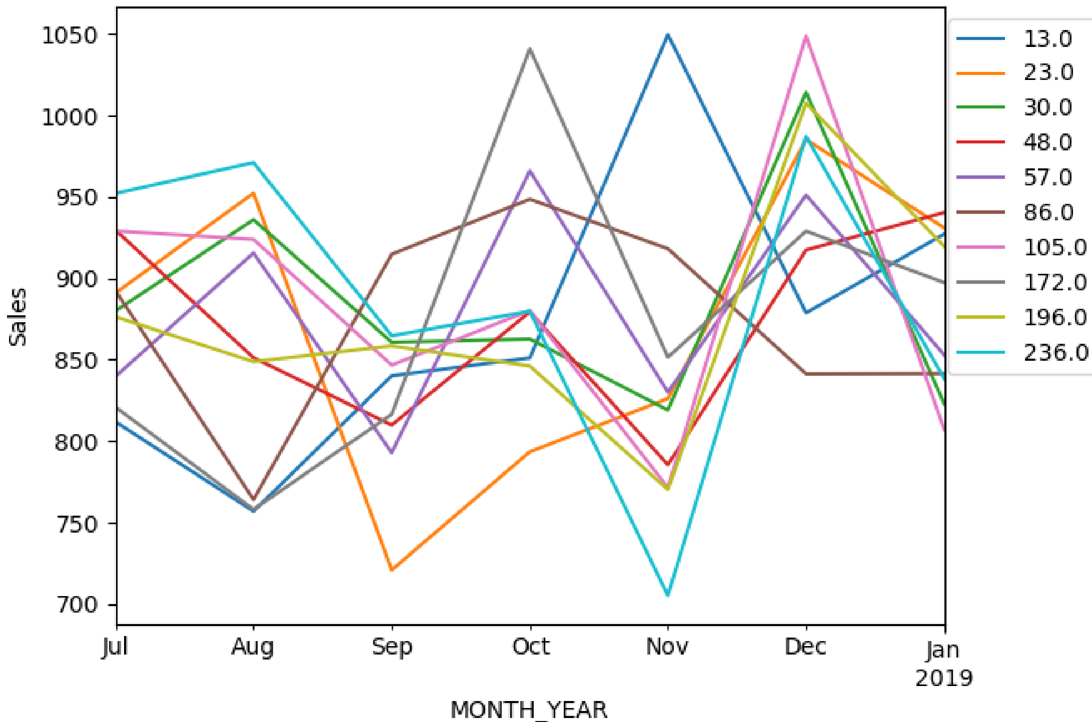
[29]:
```
# isolating the 10 stores
stores_control_2 = [13,23,30,48,57,86,105,172,196,236]
control_2 = pd.DataFrame({'Value': total_grp[stores_control_2]})
print(control_2)
```

```
                      Value
STORE_NBR MONTH_YEAR
13.0      2018-07-01  811.8
          2018-08-01  756.9
          2018-09-01  840.0
          2018-10-01  851.0
          2018-11-01 1049.4
…                     …
236.0     2018-09-01  864.6
          2018-10-01  879.6
          2018-11-01  705.2
          2018-12-01  987.0
          2019-01-01  838.2

[70 rows x 1 columns]
```

[30]:
```
# putting the 10 stores in a pivot chart format
pivot_chips_2 = control_2.pivot_table(index='MONTH_YEAR', columns='STORE_NBR',␣
  ↪values='Value')
pivot_chips_2
```

[30]:
```
STORE_NBR    13.0   23.0    30.0   48.0   57.0    86.0    105.0   172.0  \
MONTH_YEAR
2018-07-01   811.8  890.8   879.8  929.4  839.6  892.20   928.9   820.8
2018-08-01   756.9  952.1   935.8  851.1  915.4  764.05   923.7   758.0
2018-09-01   840.0  720.8   860.6  809.8  792.8  914.60   846.6   816.4
2018-10-01   851.0  793.4   862.6  879.2  965.8  948.40   880.0  1040.8
2018-11-01  1049.4  826.0   819.0  785.4  830.0  918.00   771.4   851.4
2018-12-01   878.6  985.0  1014.0  917.2  951.0  841.20  1048.6   928.8
2019-01-01   927.0  930.8   822.8  940.2  852.8  841.40   807.0   897.2

STORE_NBR    196.0  236.0
MONTH_YEAR
2018-07-01   876.2  952.0
2018-08-01   848.7  970.8
2018-09-01   858.4  864.6
2018-10-01   846.0  879.6
2018-11-01   770.2  705.2
2018-12-01  1007.4  987.0
2019-01-01   919.4  838.2
```

[31]:
```
pivot_chips_2.plot()
plt.legend(loc='upper right', bbox_to_anchor=(1.20,1))
plt.ylabel('Sales')
plt.show()
```



[32]:
```
# looking at correlation
pivot_chips_2.corr(method='pearson')
```

[32]:
```
STORE_NBR      13.0      23.0      30.0      48.0      57.0      86.0   \
STORE_NBR
13.0        1.000000 -0.150189 -0.477595 -0.310142 -0.283500  0.409610
23.0       -0.150189  1.000000  0.594336  0.620930  0.458281 -0.784698
30.0       -0.477595  0.594336  1.000000  0.292305  0.599159 -0.516913
48.0       -0.310142  0.620930  0.292305  1.000000  0.363605 -0.271147
57.0       -0.283500  0.458281  0.599159  0.363605  1.000000 -0.218110
86.0        0.409610 -0.784698 -0.516913 -0.271147 -0.218110  1.000000
105.0      -0.563172  0.558633  0.952586  0.479948  0.603628 -0.381464
172.0       0.240211 -0.115548 -0.021631  0.303527  0.593520  0.524475
196.0      -0.270657  0.600215  0.689615  0.735414  0.393114 -0.373196
236.0      -0.853592  0.515399  0.805425  0.573430  0.495600 -0.520981

STORE_NBR      105.0     172.0     196.0     236.0
STORE_NBR
```

```
13.0      -0.563172  0.240211 -0.270657 -0.853592
23.0       0.558633 -0.115548  0.600215  0.515399
30.0       0.952586 -0.021631  0.689615  0.805425
48.0       0.479948  0.303527  0.735414  0.573430
57.0       0.603628  0.593520  0.393114  0.495600
86.0      -0.381464  0.524475 -0.373196 -0.520981
105.0      1.000000  0.083882  0.739672  0.888408
172.0      0.083882  1.000000  0.239403 -0.086124
196.0      0.739672  0.239403  1.000000  0.665074
236.0      0.888408 -0.086124  0.665074  1.000000
```

Running a correlation test shows the strongest store is 172 with 0.52

Even though these 9 are the the best fit with total sales its not the best fit when it comes to sales pattern over the month. I will further explore for better option.

I want to keep it as close as possible to the total sales of 6119.85. I'll grab the next by 10 above by total sales

[33]:
```
total_sorted.iloc[180:195]
```

[33]:
```
STORE_NBR
86.0     6119.85
196.0    6126.30
57.0     6147.40
30.0     6194.60
236.0    6197.40
105.0    6206.20
91.0     6230.00
109.0    6238.30
97.0     6264.95
180.0    6265.70
102.0    6286.00
164.0    6289.40
155.0    6308.70
184.0    6309.00
160.0    6311.60
Name: TOT_SALES, dtype: float64
```

[34]:
```
# isolating the 10 stores
stores_control_3 = [86,91,97,102,109,155,160,164,180,184]
control_3 = pd.DataFrame({'Value': total_grp[stores_control_3]})
print(control_3)
```

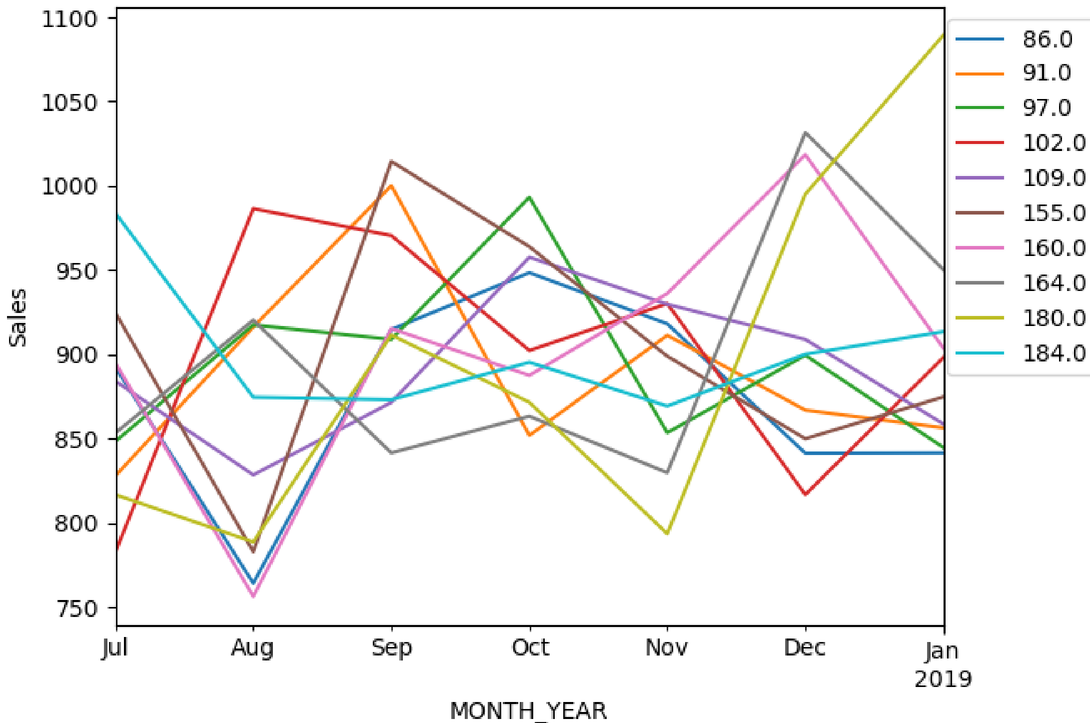
```
                      Value
STORE_NBR MONTH_YEAR
86.0      2018-07-01  892.20
          2018-08-01  764.05
```

```
           2018-09-01  914.60
           2018-10-01  948.40
           2018-11-01  918.00
…                        …
184.0      2018-09-01  873.00
           2018-10-01  895.20
           2018-11-01  869.20
           2018-12-01  900.00
           2019-01-01  913.40

[70 rows x 1 columns]
```

[35]:
```
# putting the 10 stores in a pivot chart format
pivot_chips_3 = control_3.pivot_table(index='MONTH_YEAR', columns='STORE_NBR',␣
 ↪values='Value')
pivot_chips_3
```

[35]:
```
STORE_NBR    86.0    91.0    97.0   102.0  109.0   155.0   160.0   164.0  \
MONTH_YEAR
2018-07-01  892.20   827.7  848.20  782.4  884.0   924.6   894.8   853.2
2018-08-01  764.05   916.1  917.35  986.4  828.3   782.7   756.2   920.2
2018-09-01  914.60  1000.1  908.80  970.4  871.4  1014.4   915.2   841.4
2018-10-01  948.40   851.8  993.20  902.2  957.6   963.8   887.4   863.2
2018-11-01  918.00   911.2  853.40  930.0  929.6   898.8   936.0   829.6
2018-12-01  841.20   866.8  899.40  816.6  908.8   849.8  1018.4  1031.6
2019-01-01  841.40   856.3  844.60  898.0  858.6   874.6   903.6   950.2

STORE_NBR    180.0  184.0
MONTH_YEAR
2018-07-01   816.6  983.8
2018-08-01   788.5  874.4
2018-09-01   911.4  873.0
2018-10-01   871.4  895.2
2018-11-01   793.4  869.2
2018-12-01   995.0  900.0
2019-01-01  1089.4  913.4
```

[36]:
```
pivot_chips_3.plot()
plt.legend(loc='upper right', bbox_to_anchor=(1.20,1))
plt.ylabel('Sales')
plt.show()
```



[37]:

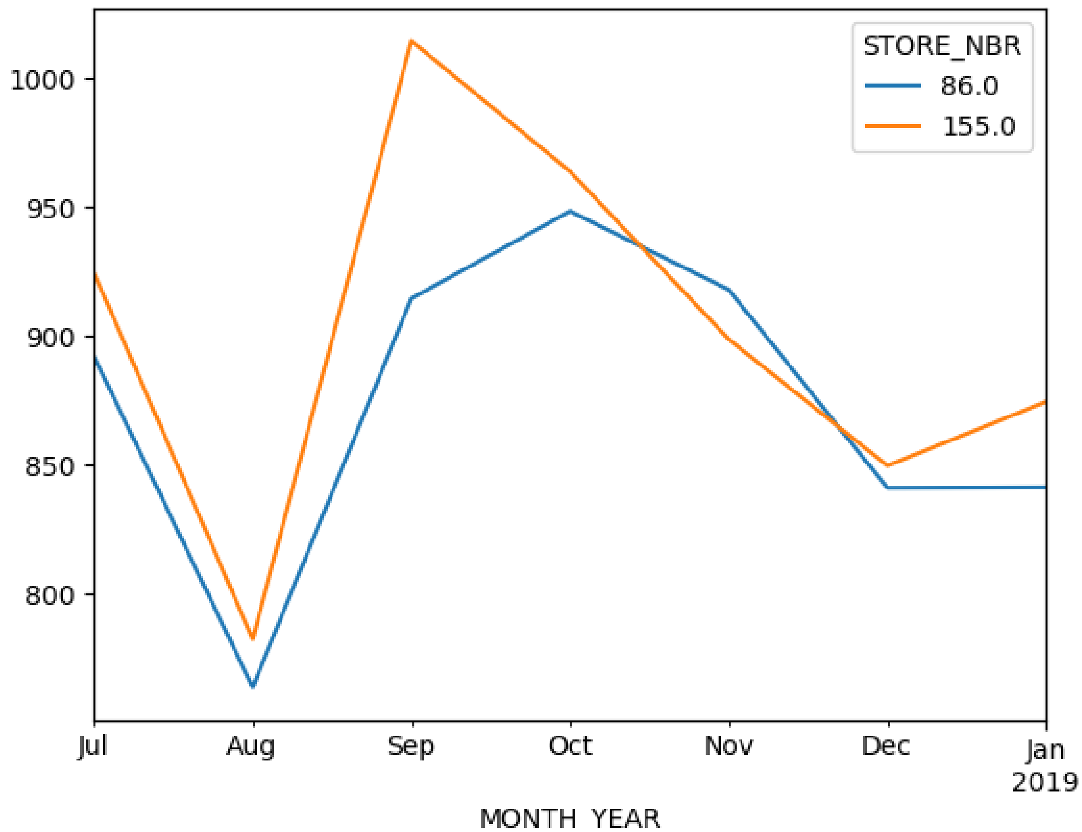
```
# looking at correlation
pivot_chips_3.corr(method='pearson')
```

[37]:

```
STORE_NBR      86.0      91.0      97.0     102.0     109.0     155.0  \
STORE_NBR
86.0       1.000000  0.019027  0.211778 -0.158172  0.788300  0.877882
91.0       0.019027  1.000000  0.107347  0.756611 -0.286609  0.285142
97.0       0.211778  0.107347  1.000000  0.296909  0.378689  0.214531
102.0     -0.158172  0.756611  0.296909  1.000000 -0.305346 -0.017878
109.0      0.788300 -0.286609  0.378689 -0.305346  1.000000  0.451168
155.0      0.877882  0.285142  0.214531 -0.017878  0.451168  1.000000
160.0      0.441970 -0.124414 -0.208412 -0.554953  0.548266  0.325977
164.0     -0.624613 -0.307085 -0.034539 -0.307030 -0.219011 -0.609502
180.0     -0.115073 -0.157871 -0.165523 -0.208742 -0.104106  0.021320
184.0      0.072641 -0.703307 -0.373501 -0.826582 -0.037604  0.074457

STORE_NBR     160.0     164.0     180.0     184.0
STORE_NBR
86.0       0.441970 -0.624613 -0.115073  0.072641
91.0      -0.124414 -0.307085 -0.157871 -0.703307
97.0      -0.208412 -0.034539 -0.165523 -0.373501
102.0     -0.554953 -0.307030 -0.208742 -0.826582
109.0      0.548266 -0.219011 -0.104106 -0.037604
```

```
155.0      0.325977 -0.609502  0.021320  0.074457
160.0      1.000000  0.296822  0.476804  0.097636
164.0      0.296822  1.000000  0.635272  0.009959
180.0      0.476804  0.635272  1.000000  0.057764
184.0      0.097636  0.009959  0.057764  1.000000
```

[38]:
```
# store 155 is very close at 0.87 correlation
store_86_155 = pivot_chips_3[[86,155]]
store_86_155.plot()
plt.show()
```



[39]:
```
# checking correlations on entire table
total_grp_df = pd.DataFrame(total_grp)

total_grp_pivot = total_grp_df.pivot_table(index='MONTH_YEAR',␣
 ↪columns='STORE_NBR', values='TOT_SALES')

total_grp_pivot_table = total_grp_pivot.corr(method='pearson')

total_grp_pivot_table[86].sort_values(ascending=False).head(10)
```

[39]:

```
STORE_NBR
31.0     1.000000
86.0     1.000000
155.0    0.877882
132.0    0.846517
240.0    0.825066
222.0    0.795075
109.0    0.788300
138.0    0.759864
198.0    0.748794
114.0    0.734415
Name: 86.0, dtype: float64
```

Lets look at the other stores by total sales before we made decision.

[41]:

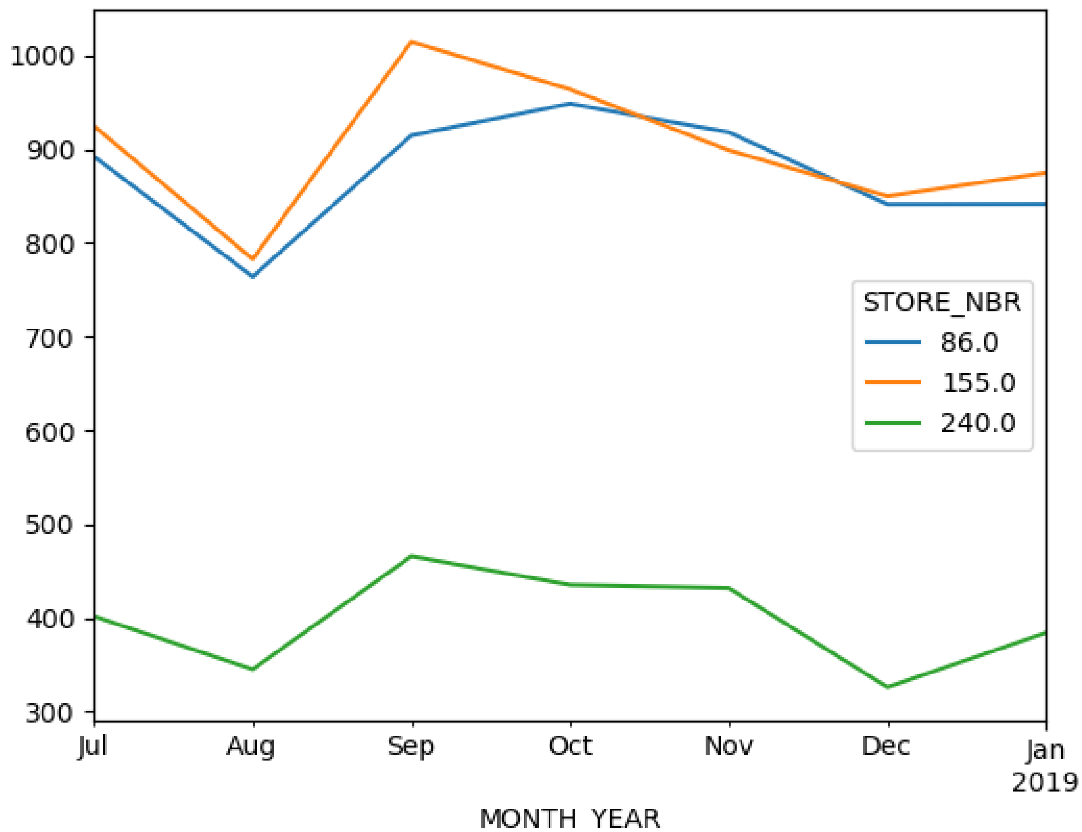
```
# grabbing the total sales sorted series to see how the sales stock up for the
↪top 4 above by strongest correlation
total_sorted.loc[[31,240,132,155]]
```

[41]:

```
STORE_NBR
31.0       14.8
240.0    2790.1
132.0     271.8
155.0    6308.7
Name: TOT_SALES, dtype: float64
```

[43]:

```
# stores 31 and 132 are way too low to use.
# grabbing stores 240,155,86 from total groub dataframe

three_stores = total_grp[[86,155,240]]

# create dataframe
three_stores_df = pd.DataFrame(three_stores)

#pivoting the dataframe
three_stores_pivot = three_stores_df.pivot_table(index='MONTH_YEAR',
↪columns='STORE_NBR', values='TOT_SALES')
three_stores_pivot.plot()
plt.show()
```



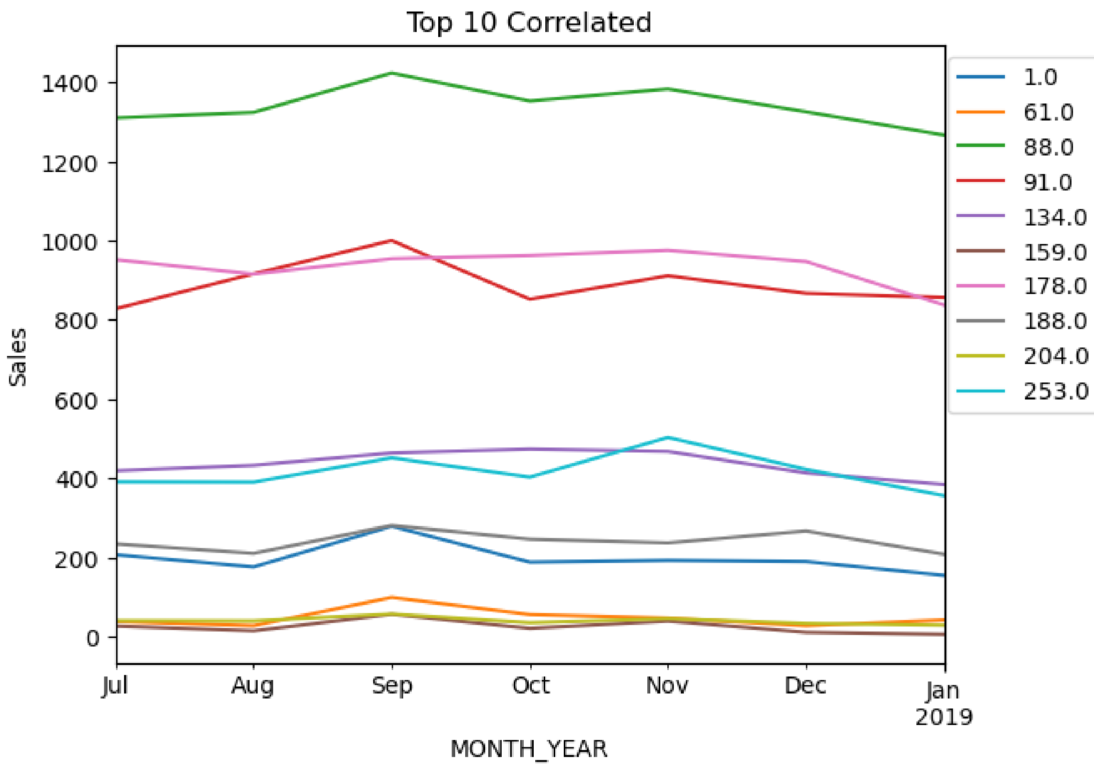
[44]:
```
# looking for control store to match with store 88
total_grp_pivot_table[88].sort_values(ascending=False).head(10)
```

[44]:
```
STORE_NBR
88.0     1.000000
159.0    0.903186
204.0    0.885774
134.0    0.864293
1.0      0.813636
253.0    0.811838
91.0     0.776688
61.0     0.748929
178.0    0.731857
188.0    0.716752
Name: 88.0, dtype: float64
```

[45]:
```
# looking at total sales
total_sorted.iloc[260:]
```

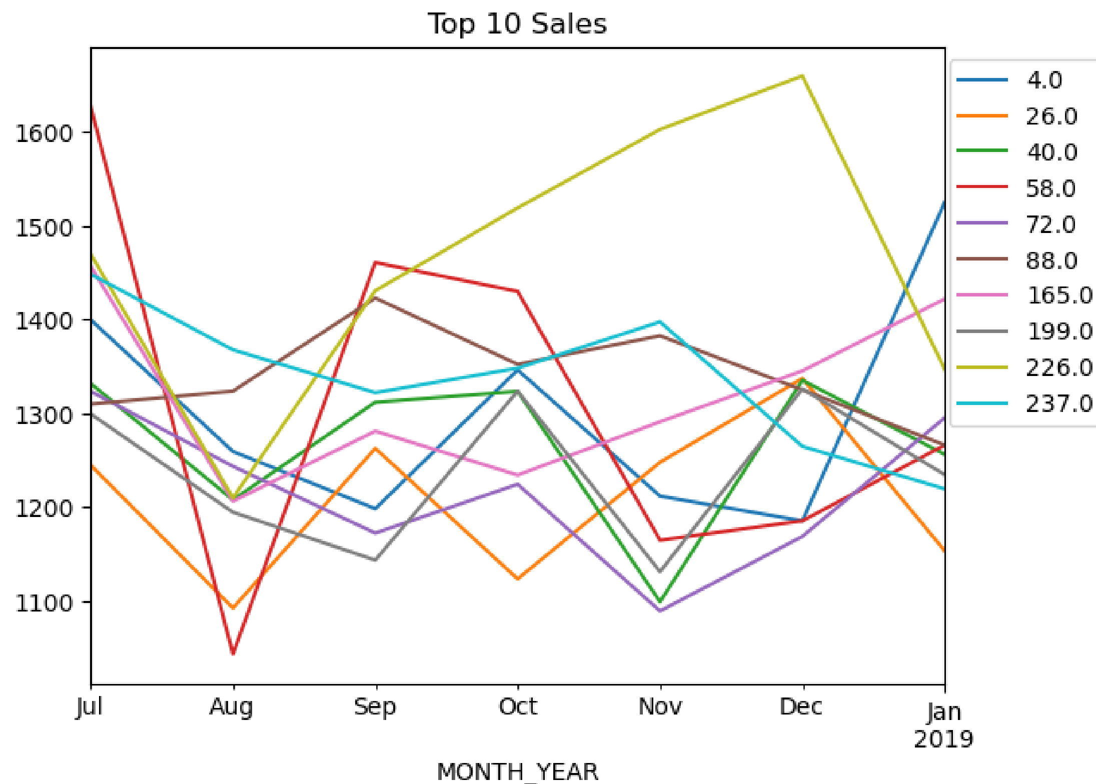
[45]:
```
STORE_NBR
26.0      8463.40
72.0      8518.50
199.0     8654.40
40.0      8866.80
203.0     8943.70
4.0       9127.00
58.0      9178.75
165.0     9237.80
237.0     9369.00
88.0      9383.60
226.0    10239.15
Name: TOT_SALES, dtype: float64
```

[48]:
```
# none of them come close to sales amount but do match the pattern
chips_4 = total_grp[[1,61,88,91,134,159,178,188,204,253]]

#create a dataframe
chips_4_df = pd.DataFrame(chips_4)

# pivoting the df
chips_4_pivot = chips_4_df.pivot_table(index='MONTH_YEAR', columns='STORE_NBR',␣
 ↪values='TOT_SALES')

chips_4_pivot.plot()
plt.title('Top 10 Correlated')
plt.ylabel('Sales')
plt.legend(loc='upper right', bbox_to_anchor=(1.20,1))
plt.show()
```



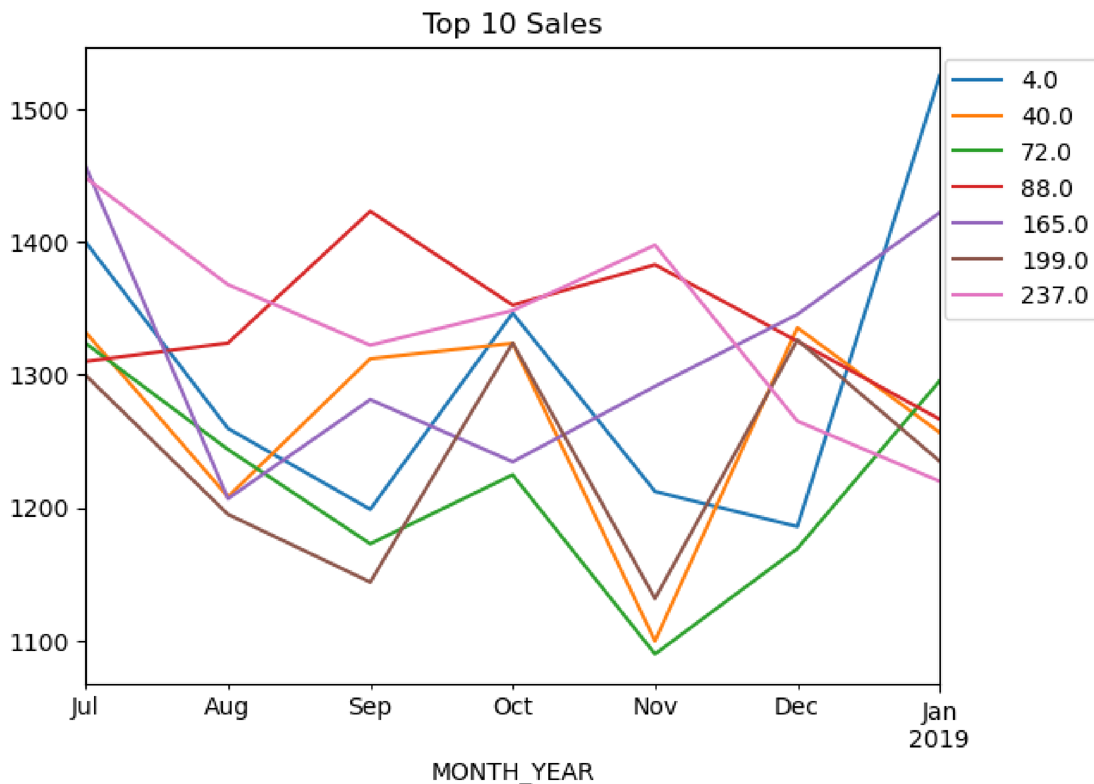
[53]:

```
# Look at the total sales top 10
chips_5 = total_grp[[4,26,40,58,72,88,165,199,226,237]]

#create a dataframe
chips_5_df = pd.DataFrame(chips_5)

# pivoting the df
chips_5_pivot = chips_5_df.pivot_table(index='MONTH_YEAR', columns='STORE_NBR',␣
↪values='TOT_SALES')

chips_5_pivot.plot()
plt.title('Top 10 Sales')
plt.legend(loc='upper right', bbox_to_anchor=(1.20,1))
plt.show()
```

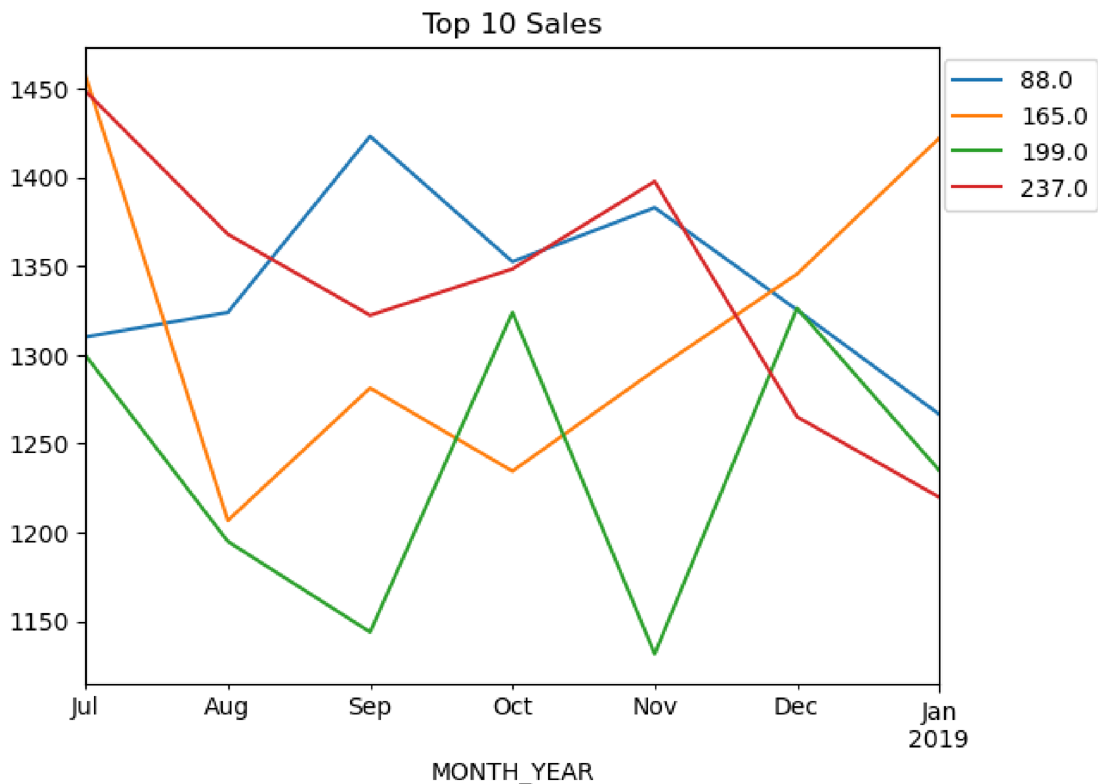


[50]:

```
# removing 3 stores to better visualize
chips_5 = total_grp[[4,40,58,72,88,165,199,237]]

#create a dataframe
chips_5_df = pd.DataFrame(chips_5)

# pivoting the df
chips_5_pivot = chips_5_df.pivot_table(index='MONTH_YEAR', columns='STORE_NBR',␣
↪values='TOT_SALES')

chips_5_pivot.plot()
plt.title('Top 10 Sales')
plt.legend(loc='upper right', bbox_to_anchor=(1.20,1))
plt.show()
```



[54]:
```
# removing 4 more  stores to better visualize
chips_5 = total_grp[[88,165,199,237]]

#create a dataframe
chips_5_df = pd.DataFrame(chips_5)

# pivoting the df
chips_5_pivot = chips_5_df.pivot_table(index='MONTH_YEAR', columns='STORE_NBR',␣
↪values='TOT_SALES')

chips_5_pivot.plot()
plt.title('Top 10 Sales')
plt.legend(loc='upper right', bbox_to_anchor=(1.20,1))
plt.show()
```



[56]:
```
# store 237 come close to the pattren of store 88
sorted_88 = total_grp_pivot_table[88].sort_values(ascending=False)
sorted_88[237]
```

[56]: 0.3084792217319044

Even though the correlation is very low at 0.30 this store makes the most sense by total sales

In top 10 sales store 237 which is the closest sales wise actually fits closest when graphed. I will procced with this store as the last control store

[58]:
```
# isolating trial time period
chips_trial = chips_final[(chips_final['MONTH_YEAR'] >= '02/2019') &␣
 ↪(chips_final['MONTH_YEAR'] <= '04/2019')]
chips_trial['MONTH_YEAR'].value_counts()
```

[58]:
```
2019-03-01    22592
2019-04-01    21766
2019-02-01    20405
Name: MONTH_YEAR, dtype: int64
```

[59]:
```python
# creating new df for trial and control stores
tstore_77 = chips_trial[chips_trial['STORE_NBR'] == 77]
cstore_233 = chips_trial[chips_trial['STORE_NBR'] == 233]

tstore_86 = chips_trial[chips_trial['STORE_NBR'] == 86]
cstore_155 = chips_trial[chips_trial['STORE_NBR'] == 155]

tstore_88 = chips_trial[chips_trial['STORE_NBR'] == 88]
cstore_237 = chips_trial[chips_trial['STORE_NBR'] == 237]

tstore_77
```

[59]:
```
        SHORT_DATE  STORE_NBR  LYLTY_CARD_NBR   TXN_ID              LIFESTAGE  \
1438    2019-03-28       77.0         77000.0  74911.0  MIDAGE SINGLES/COUPLES
1439    2019-04-13       77.0         77000.0  74912.0  MIDAGE SINGLES/COUPLES
1441    2019-03-03       77.0         77063.0  74977.0  MIDAGE SINGLES/COUPLES
1442    2019-02-20       77.0         77069.0  74985.0  MIDAGE SINGLES/COUPLES
1443    2019-03-08       77.0         77069.0  74986.0  MIDAGE SINGLES/COUPLES
…              …        …              …        …                     …
260449 2019-03-14       77.0         77068.0  74984.0   YOUNG SINGLES/COUPLES
260452 2019-02-03       77.0         77120.0  75047.0   YOUNG SINGLES/COUPLES
260454 2019-03-27       77.0         77141.0  75069.0   YOUNG SINGLES/COUPLES
260459 2019-04-20       77.0         77371.0  75308.0   YOUNG SINGLES/COUPLES
260464 2019-03-03       77.0         77429.0  75373.0   YOUNG SINGLES/COUPLES

       PREMIUM_CUSTOMER  PROD_NBR                               PROD_NAME  \
1438             Budget      18.0          Cheetos Chs & Bacon Balls 190g
1439             Budget      69.0   Smiths Chip Thinly  S/Cream&Onion 175g
1441             Budget     112.0   Tyrrells Crisps     Ched & Chives 165g
1442             Budget      98.0   NCC Sour Cream &    Garden Chives 175g
1443             Budget       8.0  Smiths Crinkle Cut  Chips Original 170g
…                   …       …                                        …
260449          Premium      79.0   Smiths Chip Thinly  CutSalt/Vinegr175g
260452          Premium      28.0     Thins Potato Chips  Hot & Spicy 175g
260454          Premium      82.0    Smith Crinkle Cut    Mac N Cheese 150g
260459          Premium      54.0                       CCs Original 175g
260464          Premium      21.0   WW Sour Cream &OnionStacked Chips 160g

             BRAND WEIGHT  PROD_QTY  TOT_SALES BAG_SIZE MONTH_YEAR
1438       Cheetos   190g       1.0        3.3    Small 2019-03-01
1439        Smiths   175g       1.0        3.0    Small 2019-04-01
1441      Tyrrells   165g       2.0        8.4    Small 2019-03-01
1442       Natural   175g       2.0        6.0    Small 2019-02-01
1443        Smiths   170g       2.0        5.8    Small 2019-03-01
…             …     …         …          …       …          …
260449      Smiths   175g       1.0        3.0    Small 2019-03-01
260452       Thins   175g       2.0        6.6    Small 2019-02-01
```

```
260454      Smiths   150g       2.0         5.2    Small 2019-03-01
260459         CCs   175g       2.0         4.2    Small 2019-04-01
260464  Woolworths   160g       2.0         3.8    Small 2019-03-01

[148 rows x 14 columns]
```

[60]:
```
# lets start with store 77 and 233 looking at total sales and product sold
tstore_77[['TOT_SALES', 'PROD_QTY']].sum()
```

[60]:
```
TOT_SALES    777.0
PROD_QTY     234.0
dtype: float64
```

[61]:
```
cstore_233[['TOT_SALES', 'PROD_QTY']].sum()
```

[61]:
```
TOT_SALES    601.7
PROD_QTY     175.0
dtype: float64
```

[62]:
```
#looking at repeat customers for trial store
tstore_77['LYLTY_CARD_NBR'].value_counts()
```

[62]:
```
77000.0    2
77007.0    2
77454.0    2
77009.0    2
77115.0    2
          ..
77480.0    1
77478.0    1
77344.0    1
77105.0    1
77429.0    1
Name: LYLTY_CARD_NBR, Length: 124, dtype: int64
```

[65]:
```
# total customer transactions
tstore_77[['LYLTY_CARD_NBR']].count()
```

[65]:
```
LYLTY_CARD_NBR    148
dtype: int64
```

[66]:
```
cstore_233[['LYLTY_CARD_NBR']].count()
```

[66]:
```
LYLTY_CARD_NBR    121
dtype: int64
```

[67]:
```
#looking at repeat customers for control store
cstore_233['LYLTY_CARD_NBR'].value_counts()
```

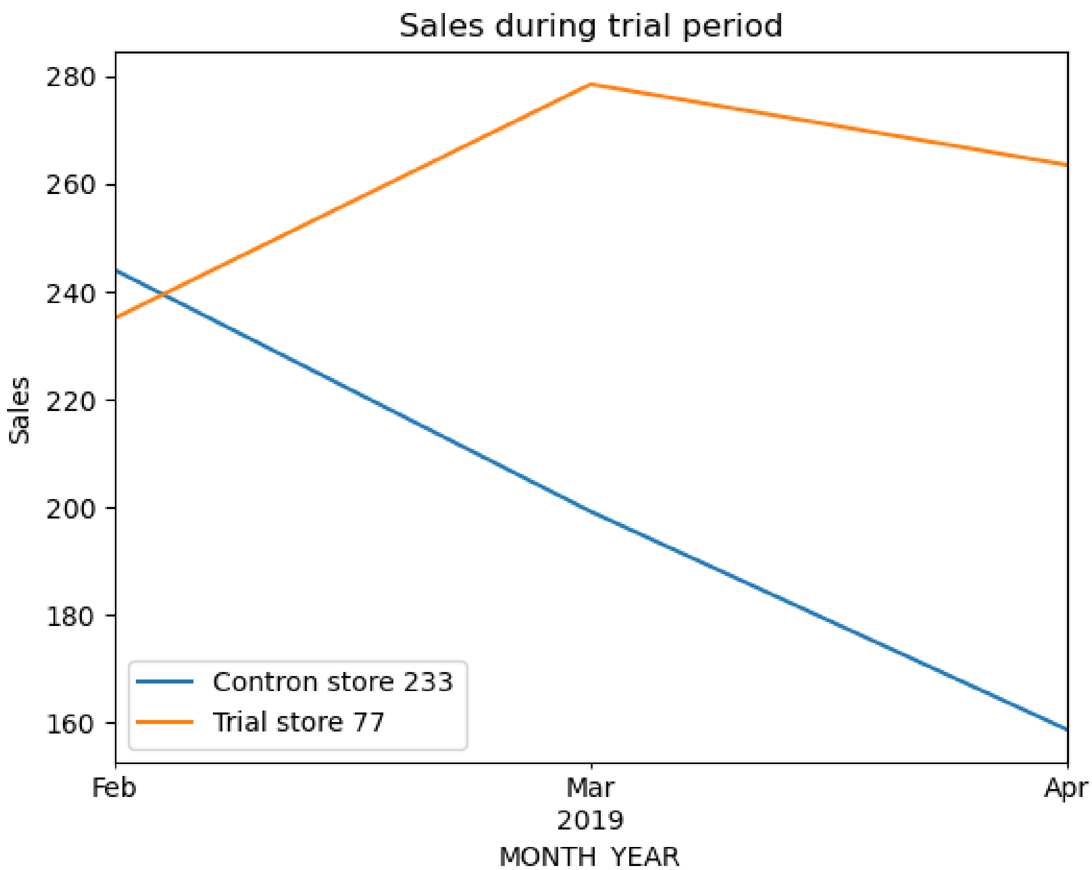
[67]:
```
233398.0    2
233227.0    2
233449.0    2
233111.0    2
233071.0    2
           ..
233139.0    1
233451.0    1
233290.0    1
233221.0    1
233038.0    1
Name: LYLTY_CARD_NBR, Length: 112, dtype: int64
```

[68]:
```python
# counting repeat customer that purchased more than once
repeat_customers = tstore_77['LYLTY_CARD_NBR'].value_counts()

print(repeat_customers.head(24))

repeat_customers = 24
```

```
77000.0    2
77007.0    2
77454.0    2
77009.0    2
77115.0    2
77139.0    2
77450.0    2
77466.0    2
77206.0    2
77207.0    2
77389.0    2
77482.0    2
77338.0    2
77359.0    2
77424.0    2
77077.0    2
77341.0    2
77462.0    2
77420.0    2
77402.0    2
77069.0    2
77350.0    2
77123.0    2
77045.0    2
Name: LYLTY_CARD_NBR, dtype: int64
```

[69]:
```
# grouping stores by month year
grouped_77 = tstore_77.groupby('MONTH_YEAR')
grouped_233 = cstore_233.groupby('MONTH_YEAR')
```

[71]:
```
grouped_233['TOT_SALES'].sum().plot(label= 'Contron store 233')
grouped_77['TOT_SALES'].sum().plot(label= 'Trial store 77')
plt.ylabel('Sales')
plt.legend()
plt.title('Sales during trial period')
plt.show()
```



[72]:
```
# lets start with store 86 and 155 looking at total sales and product sold
tstore_86[['TOT_SALES', 'PROD_QTY']].sum()
```

[72]:
```
TOT_SALES    2788.2
PROD_QTY      815.0
dtype: float64
```

[73]:
```
cstore_155[['TOT_SALES', 'PROD_QTY']].sum()
```

[73]:
```
TOT_SALES    2540.2
PROD_QTY      736.0
dtype: float64
```

[74]:
```
#looking at repeat customers for trial store
tstore_86['LYLTY_CARD_NBR'].value_counts()
```

[74]:
```
86112.0    6
86075.0    5
86116.0    5
86230.0    5
86172.0    5
          ..
86010.0    1
86205.0    1
86203.0    1
86013.0    1
86237.0    1
Name: LYLTY_CARD_NBR, Length: 215, dtype: int64
```

[75]:
```
# total customer transactions
tstore_86[['LYLTY_CARD_NBR']].count()
```

[75]:
```
LYLTY_CARD_NBR    408
dtype: int64
```

[76]:
```
cstore_155[['LYLTY_CARD_NBR']].count()
```

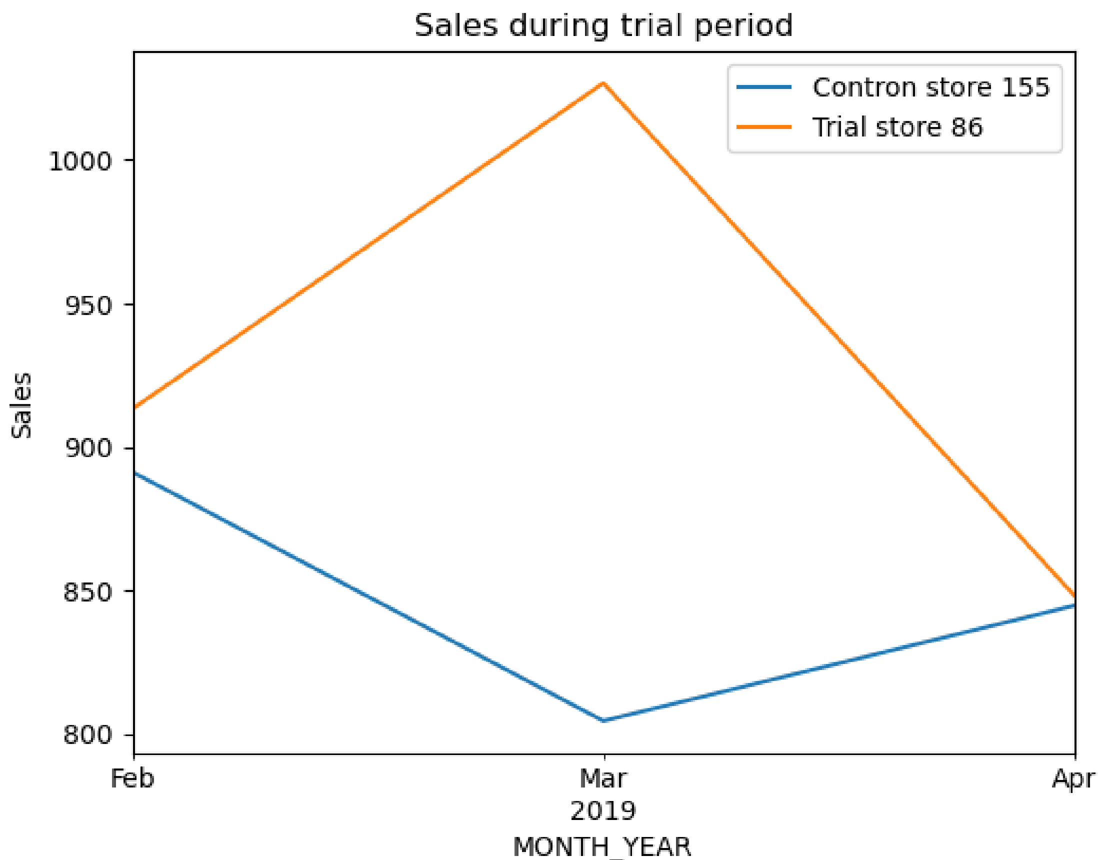
[76]:
```
LYLTY_CARD_NBR    368
dtype: int64
```

[77]:
```
#looking at repeat customers for control store
cstore_155['LYLTY_CARD_NBR'].value_counts()
```

[77]:
```
155082.0    5
155010.0    5
155153.0    5
155048.0    5
155014.0    4
           ..
155174.0    1
155171.0    1
155157.0    1
155160.0    1
155152.0    1
Name: LYLTY_CARD_NBR, Length: 190, dtype: int64
```

[78]:
```
# grouping stores by month year
grouped_86 = tstore_86.groupby('MONTH_YEAR')
grouped_155 = cstore_155.groupby('MONTH_YEAR')
```

[79]:
```
grouped_155['TOT_SALES'].sum().plot(label= 'Contron store 155')
grouped_86['TOT_SALES'].sum().plot(label= 'Trial store 86')
plt.ylabel('Sales')
plt.legend()
plt.title('Sales during trial period')
plt.show()
```



[80]:
```
# lets start with store 88 and 237 looking at total sales and product sold
tstore_88[['TOT_SALES', 'PROD_QTY']].sum()
```

[80]:
```
TOT_SALES    4286.8
PROD_QTY      972.0
dtype: float64
```

[81]:
```
cstore_237[['TOT_SALES', 'PROD_QTY']].sum()
```

[81]:
```
TOT_SALES    3817.6
PROD_QTY      860.0
dtype: float64
```

[82]:
```
#looking at repeat customers for trial store
tstore_88['LYLTY_CARD_NBR'].value_counts()
```

[82]:
```
88313.0    6
88231.0    5
88259.0    4
88114.0    4
88105.0    4
          ..
88236.0    1
88256.0    1
88258.0    1
88315.0    1
88127.0    1
Name: LYLTY_CARD_NBR, Length: 261, dtype: int64
```

[83]:
```
# total customer transactions
tstore_88[['LYLTY_CARD_NBR']].count()
```

[83]:
```
LYLTY_CARD_NBR    486
dtype: int64
```

[84]:
```
cstore_237[['LYLTY_CARD_NBR']].count()
```

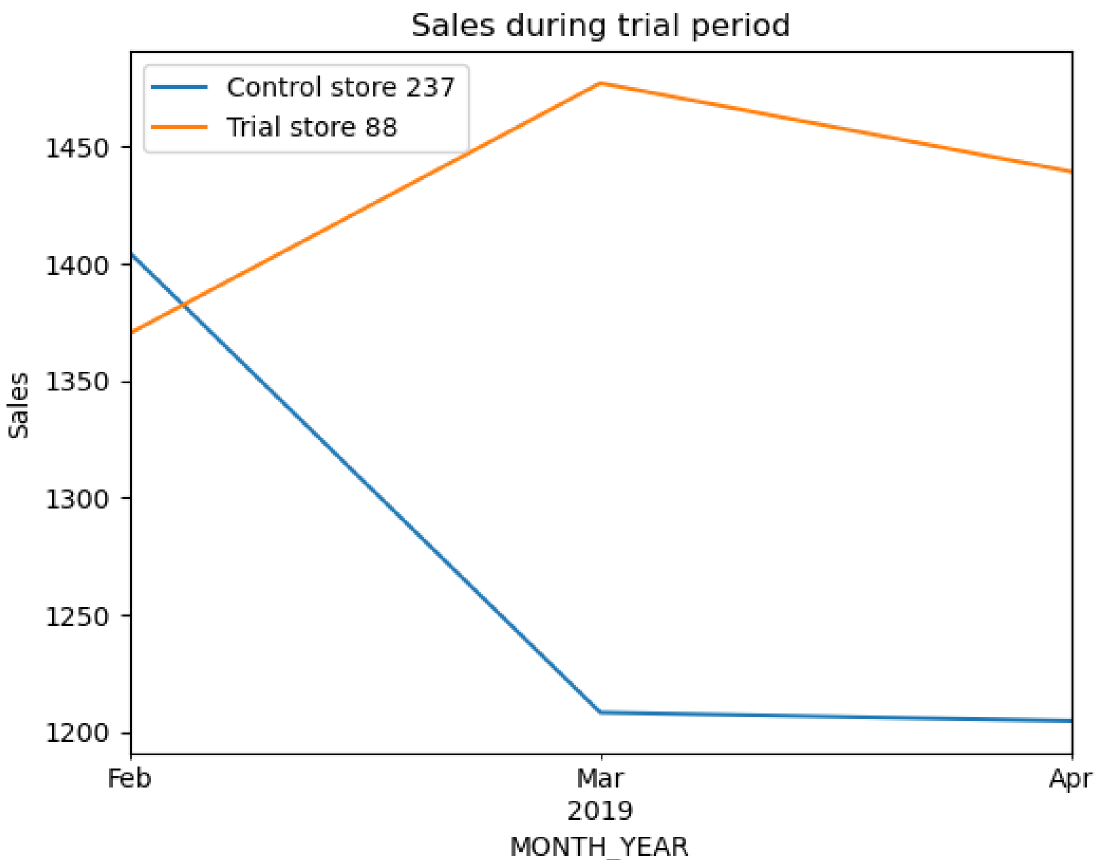
[84]:
```
LYLTY_CARD_NBR    430
dtype: int64
```

[85]:
```
#looking at repeat customers for control store
cstore_237['LYLTY_CARD_NBR'].value_counts()
```

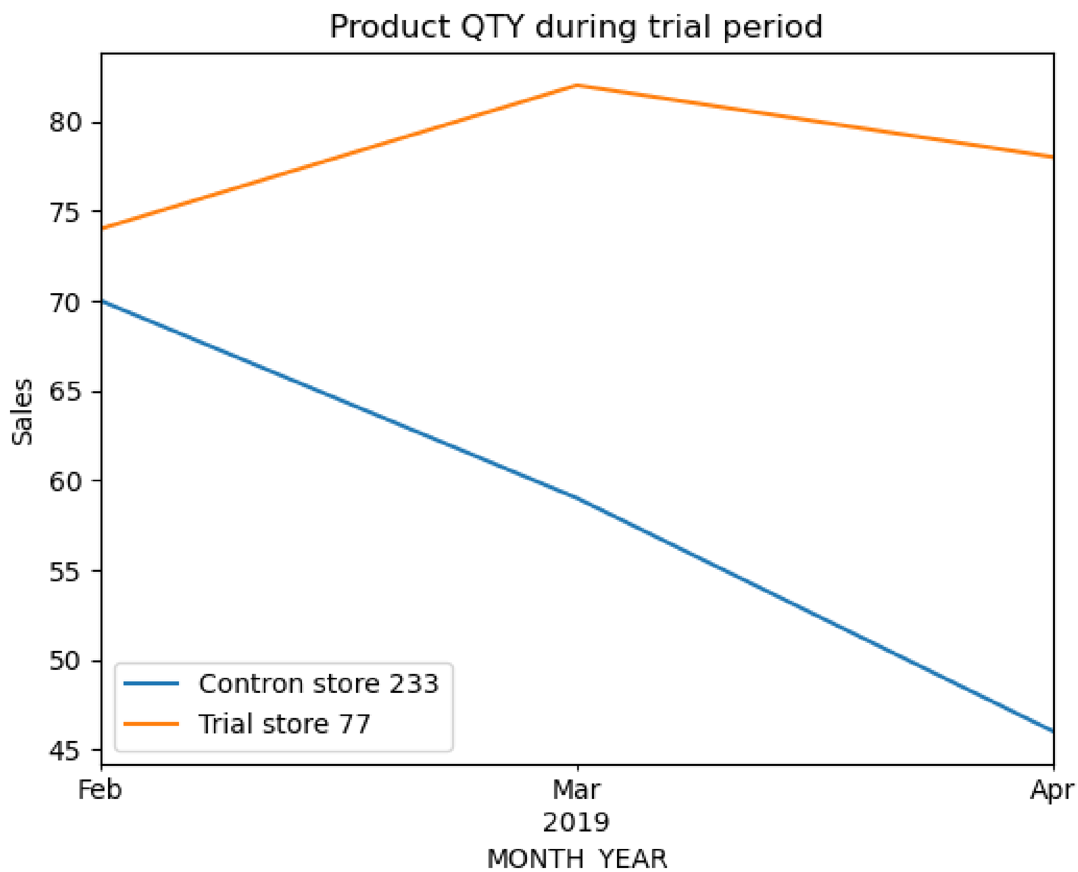
[85]:
```
237366.0    6
237182.0    5
237325.0    5
237038.0    5
237234.0    4
           ..
237357.0    1
237358.0    1
237382.0    1
237054.0    1
237345.0    1
Name: LYLTY_CARD_NBR, Length: 262, dtype: int64
```

[89]:
```
# grouping stores by month year
grouped_88 = tstore_88.groupby('MONTH_YEAR')
grouped_237 = cstore_237.groupby('MONTH_YEAR')
```

[90]:
```
grouped_237['TOT_SALES'].sum().plot(label= 'Control store 237')
grouped_88['TOT_SALES'].sum().plot(label= 'Trial store 88')
plt.ylabel('Sales')
plt.legend()
plt.title('Sales during trial period')
plt.show()
```

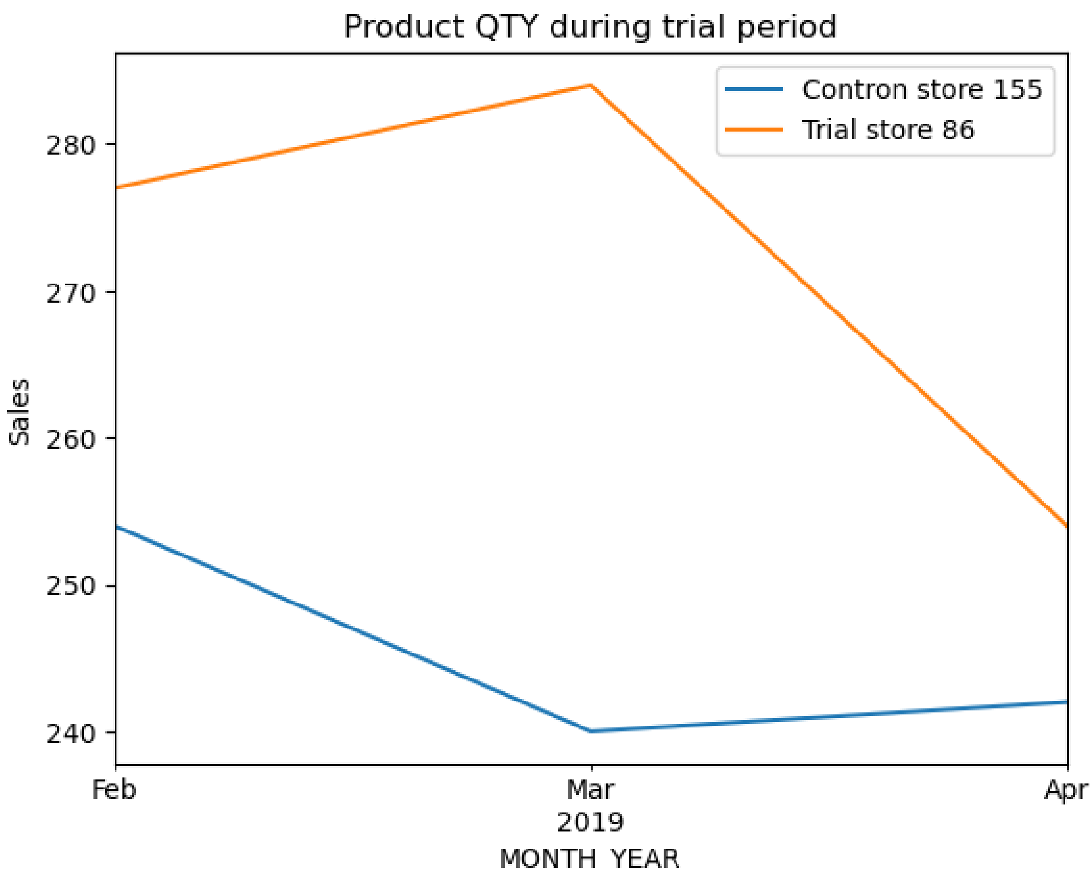


[92]:
```
# lets visualize the product QTY during the trial period for each group
grouped_233['PROD_QTY'].sum().plot(label= 'Contron store 233')
grouped_77['PROD_QTY'].sum().plot(label= 'Trial store 77')
plt.ylabel('Sales')
plt.legend()
plt.title('Product QTY during trial period')
plt.show()
```

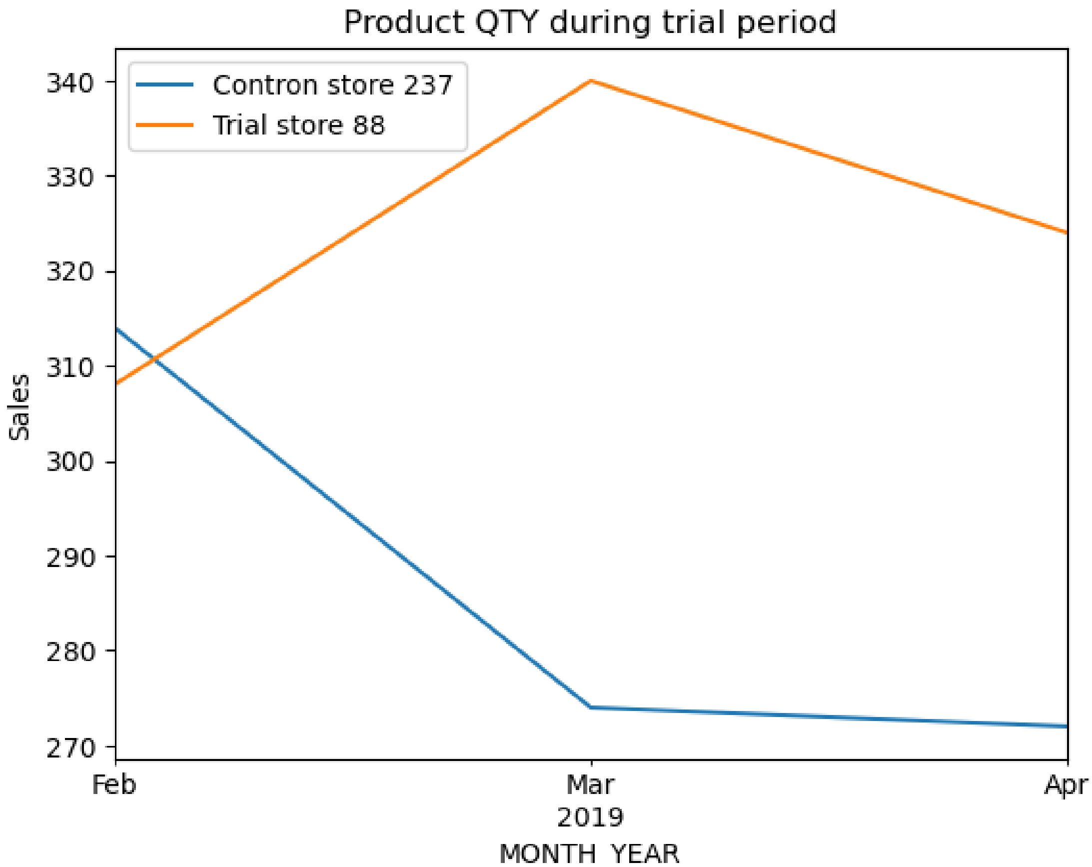


[93]:

```
grouped_155['PROD_QTY'].sum().plot(label= 'Contron store 155')
grouped_86['PROD_QTY'].sum().plot(label= 'Trial store 86')
plt.ylabel('Sales')
plt.legend()
plt.title('Product QTY during trial period')
plt.show()
```



[94]:
```
grouped_237['PROD_QTY'].sum().plot(label= 'Contron store 237')
grouped_88['PROD_QTY'].sum().plot(label= 'Trial store 88')
plt.ylabel('Sales')
plt.legend()
plt.title('Product QTY during trial period')
plt.show()
```



[95]:
```
# lets see how they stack up with average transactions per customers
grouped_77['LYLTY_CARD_NBR'].value_counts().mean()
```

[95]: 1.0422535211267605

[96]:
```
grouped_233['LYLTY_CARD_NBR'].value_counts().mean()
```

[96]: 1.0521739130434782

[97]:
```
grouped_86['LYLTY_CARD_NBR'].value_counts().mean()
```

[97]: 1.2477064220183487

[98]:
```
grouped_155['LYLTY_CARD_NBR'].value_counts().mean()
```

[98]: 1.2777777777777777

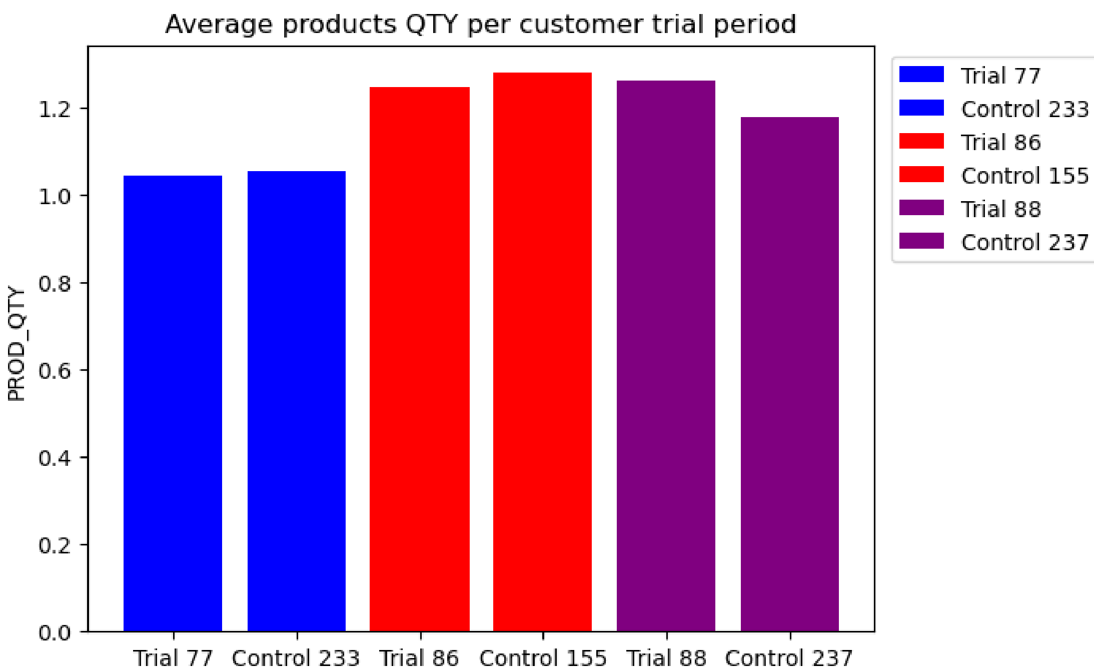
[99]:
```
grouped_88['LYLTY_CARD_NBR'].value_counts().mean()
```

[99]: 1.2590673575129534

[100]:
```python
grouped_237['LYLTY_CARD_NBR'].value_counts().mean()
```

[100]: 1.178082191780822

[104]:
```python
groups_1 = ['Trial 77', 'Control 233']
groups_2 = ['Trial 86', 'Control 155']
groups_3 = ['Trial 88', 'Control 237']

value_grp_1 = [1.042, 1.052]
value_grp_2 = [1.247, 1.277]
value_grp_3 = [1.259, 1.178]

plt.bar(groups_1, value_grp_1, label= groups_1, color = 'blue')
plt.bar(groups_2, value_grp_2, label= groups_2, color = 'red')
plt.bar(groups_3, value_grp_3, label= groups_3, color = 'purple')
plt.ylabel('PROD_QTY')
plt.legend(loc = 'upper right', bbox_to_anchor=(1.30,1))
plt.title('Average products QTY per customer trial period')
plt.show()
```



Comparing the trial stores to control stores the trial stores are outperforming the control stores during this period

My recommendation would be to increase the amount of trial store and do another analysis after 3 month to see if the increased sales stay true and stablize at the higher

point.

[105]:
```
chips_final.to_csv('chips_final.csv')
```

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