case_study_part_1_Rondell-Copy2

February 16, 2019

1 Problem 1 from MS Case Study

1.0.1 Rondell King

Background You work at a magic potato trading company. The company earns fees by storing potatoes for clients as well as finding buyers and sellers of potatoes on behalf of clients. The storage fees earned by the company are based off the total market value of the potatoes stored by the clients. These potatoes are magic- they do not spoil while in storage, they can be shrunk so they take up very little space, and the delivery of the potatoes does not incur any cost. Potatoes must be kept separate from each other and therefore the cost to store different potato types may differ. Storage rates will be determined by traders and based off of numerous factors.
You work on the data science team and your role is to work with data to create reports, models, and make the business smarter and more efficient Two parts Analyse the given sets of data and answer the questions below. Help the management team understand what is happening in the potato market and what client activity looks like. Create a web tool that helps capture and save potato prices seen in the market

Part 1 Background You are given the Data_Files excel sheet which contains information about potatoes, the company's clients, and a snapshot of client potato positions for a period of time. A quantity of Null represents no position. Management has some questions regarding these data and would like to know your interpretations. You will present your findings at the quarterly management meeting.

Questions * Which clients have the largest potato stockpile based on market value? * Which clients are the most active? * Which potatoes are most activity traded? * What client activity trends do you see? * What potato price trends do you see? * Are there any factors that can help predict potato prices? * Are there any factors that can help predict client activity? * Summarize what has happened during this period

2 First Step is to load the excel sheets using Pandas.

Examine the data and check for missing values in the tables.

```
In [25]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
         %matplotlib inline
```

```python
###
### LOAD AND SANITIZE DATA###
###

# Load xls sheets into dataframes
data_file = '2_Data_Files.xlsx'  # File must be in the same directory as this script

# Each sheet will be stored in the dict as a dataframe object
df_dict = pd.read_excel(data_file, sheetname=['Potatoes_Info', 'Client_Info', 'Potatoes
positions = df_dict.get('Potatoes_Positions')  # Trade data from 5/1/2020 to 8/31/2020.
client_info = df_dict.get('Client_Info')  # Key = Client ID
potato_info = df_dict.get('Potatoes_Info')  # Ket = Product ID

# Merge the sheets into one dataframe object.
positions_merged = positions.merge(client_info, on='Client ID')
positions_merged = positions_merged.merge(potato_info, on='Product ID')

# Sanitize the Data by replacing [NULL] with 0 (A value of [NULL] represents no positio


print(positions_merged.isnull().sum())#213 prices are missing.
```

```
/anaconda3/lib/python3.7/site-packages/pandas/io/excel.py:329: FutureWarning: The `sheetname` ke
  **kwds)


Date                              0
Client ID                         0
Product ID                        0
Price                           213
Quantity                          0
First Name                        0
Last Name                         0
Client Type                       0
Client Location                   0
Variety Name                      0
Country                           0
Shape of tuber                    0
Colour of skin                    0
Colour of flesh                   0
Depth of eyes                     0
Smoothness of skin                0
Colour of base of lightsprout     0
Maturity                          0
Height of plants                  0
Frequency of berries              0
dtype: int64
```

2.0.1 Convert Null prices to 0

```
In [26]: positions_merged['Quantity'].replace('[NULL]', 0, inplace=True)
```

3 Which clients have the largest potato stockpile based on market value?

Top 3 Clients in terms of market value are:

1. Destiny
2. Jamel

3. Samuel

I found the top market value by adding a new column to the dataframe.
Price X Quantity = Market Value
Sorting the table by Market value shows the clients with the highest Totals.

```
In [27]: # Add new column for Market value => Price * Quantity.
         positions_merged['Market Value'] = positions_merged.Price * positions_merged.Quantity
         positions_merged['Market Value'].fillna(0,inplace=True)

         # Aggregate on client ID to find the clients with highest market value.
         top_market_value = positions_merged.groupby(['Client ID',
                                                      'First Name ',
                                                       'Last Name'], as_index=False)['Market Val
         top_market_value = top_market_value[['Client ID','First Name ','Last Name', 'Market Val
                                                                                  ascending=False)

         print(top_market_value.to_string(formatters={'Market Value':'${:,.2f}'.format}))
```

```
    Client ID First Name      Last Name          Market Value
4          27      Destiny     Aldridge $227,333,258,486.22
7          38        Jamel       Caruso   $4,099,865,425.30
21         82       Samuel       Cheney     $381,338,437.50
18         74      Nakisha  Southerland     $253,565,363.06
5          30      Eulalia       Culver     $178,615,864.61
22         89      Tammera     Lassiter      $77,000,752.74
9          44       Jeremy         Kong      $68,287,532.35
13         50       Landon         Kyle      $47,785,223.01
23         94       Valeri   Burchfield      $47,421,539.53
0          17         Chan          Vue      $38,883,442.46
12         49      Kirstin       Browne      $34,918,354.53
14         52       Larita     Albright      $27,403,986.45
16         64       Mariko        Giles      $20,889,961.86
19         77     Rasheeda       Spivey      $16,789,133.46
20         78      Rashida      Proctor       $6,808,320.95
2          21        Chase        Woody       $1,765,570.00
```

```
3           24        Daine    Gustafson      $1,068,943.80
15          59      Loraine    Mcdermott        $995,961.26
6           33    Georgiana         Moya        $432,154.95
17          65        Maura      Jeffrey        $359,841.62
8           41        Jeane      Peoples        $336,669.20
10          45       Kazuko      Steward        $105,272.75
11          47        Kiera       Staton              $0.00
1           18    Chantelle      Hollins              $0.00
```

4 Which clients are the most active?

Count how many times the client name is in the positions data. Get a count of unique values for First Name

Below are the are names of the 10 most active clients and their total trades during this period.

```
In [28]: client_acitivty = positions_merged.groupby(['Client ID',
                                                 'First Name ',
                                                 'Last Name'])['Date'].count()
         client_acitivty.sort_values(ascending=False).head(10)
```

```
Out[28]: Client ID  First Name   Last Name
         38         Jamel        Caruso         10239
         74         Nakisha      Southerland     3575
         50         Landon       Kyle            2091
         94         Valeri       Burchfield      1729
         64         Mariko       Giles           1636
         44         Jeremy       Kong            1629
         27         Destiny      Aldridge        1202
         17         Chan         Vue              961
         89         Tammera      Lassiter         879
         30         Eulalia      Culver           740
         Name: Date, dtype: int64
```

5 Which potatoes are most actively traded?

30 Most actively traded potatoes and their trade count.

```
In [29]: potato_trade_activity = positions_merged.groupby(['Product ID',
                                                 'Variety Name'])['Date'].count()
         potato_trade_activity.sort_values(ascending=False).head(30)
```

```
Out[29]: Product ID  Variety Name
         16          Argos                724
         172         Lorimer              682
         45          British Queen        615
         93          Edzell Blue          611
```

```
10          Amorosa          582
19          Arran Banner     548
281         Shepody          514
100         Emma             511
14          Anya             482
7           Ambassador       480
251         Rocket           474
2           Accord           471
28          Atlantic         461
57          Carnaval         422
102         Erntestolz       404
73          Colleen          401
98          Emblem           384
218         Pentland Dell    383
15          Apache           382
145         Jubilee          377
122         Gourmandine      372
36          Barna            358
217         Pentland Crown   354
278         Shannon          343
81          Cultra           339
17          Ariata           333
254         Roscor           319
23          Arrow            317
83          Desiree          308
230         Pizazz           305
Name: Date, dtype: int64
```

6 What client activity trends do you see?

Client activity is the lowest during May and peaks in June. Throughout August begins to taper out. Seasonality plays a role here, where it appears the market for potatoes experiences peak activity during the summer season.

In August client activity is relatively low when compared to Jun and July but there is much less volatility in activty during August. Between May and July, trade volume swings are much more intense.

Highest trade activity count:404 occurs on 2020-06-12

Lowest trade activity count:232 occurs on 2020-05-05

In [41]:
```
# Max and min trade activity
import seaborn as sns
sns.set(rc={'figure.figsize':(30,20)})
max_trds = positions_merged['Date'].value_counts().max()
min_trds = positions_merged['Date'].value_counts().min()
max_date = positions_merged['Date'].value_counts().idxmax()
min_date = positions_merged['Date'].value_counts().idxmin()
```

```
print("Highest trade activity count:{} occurs on {}".format(max_trds, max_date))
print("Lowest trade activity count:{} occurs on {}".format(min_trds, min_date))

activity_plt = positions_merged['Date'].value_counts().plot(title = 'Trade Activity')
activity_plt. set_xlabel('Trade Date', fontsize=15)

client_activity_table = positions_merged.set_index('Date')
```

```
Highest trade activity count:404 occurs on 2020-06-12 00:00:00
Lowest trade activity count:232 occurs on 2020-05-05 00:00:00
```

7 What potato price trends do you see?

Generally speaking you can use seasonality to help predict potato prices as it seems, there are times,

when the price increases drastically for the entire market (Jun/July) and it drops significantly in May.

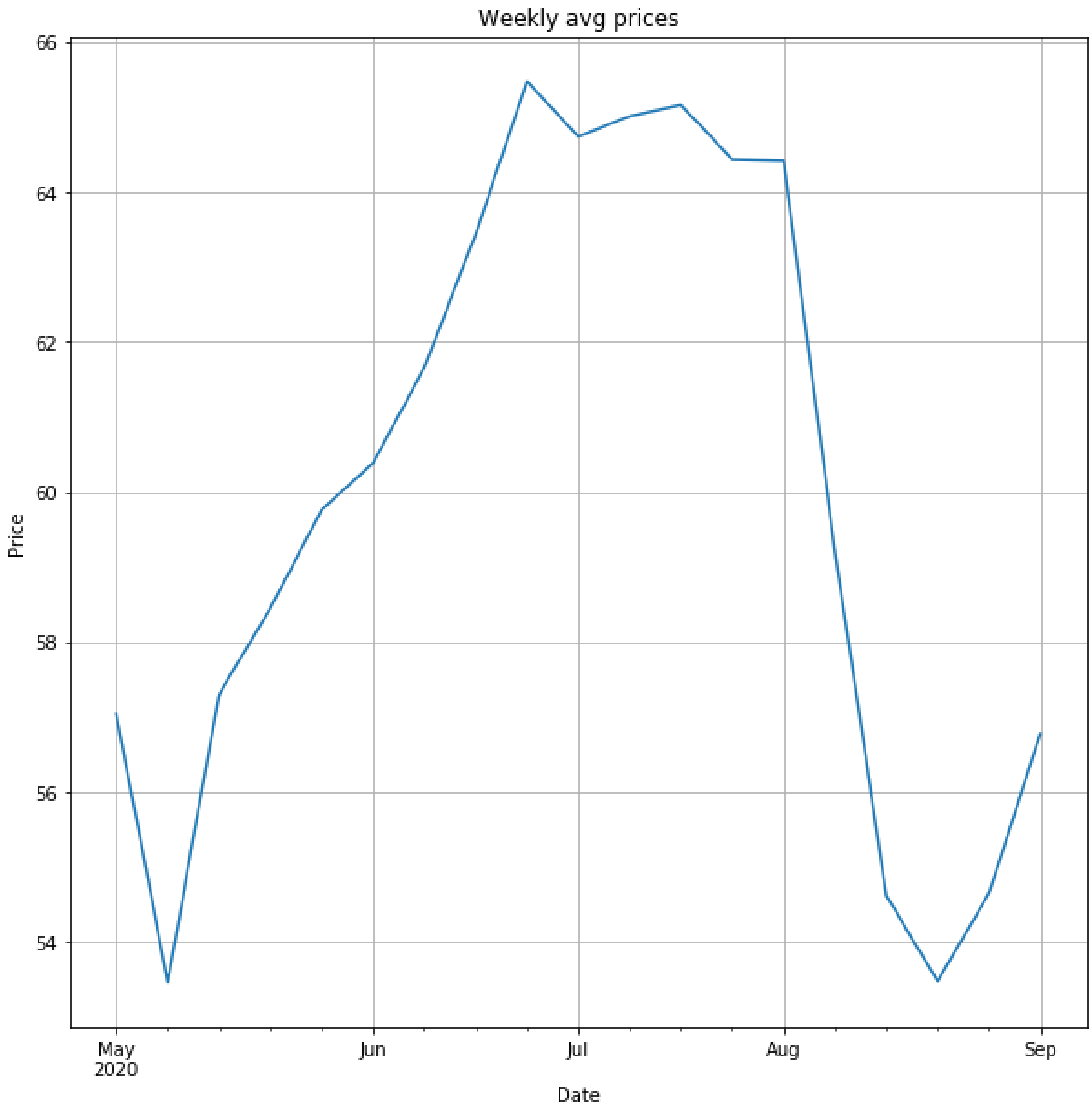
Below you can view a plot for the weekly average potato prices across the sector.

```
In [9]: # Add a millisecond to each date to create a unique index. This allows us to turn the pr
        positions_merged['Date'] = positions_merged['Date'] + \
                                   pd.to_timedelta(positions_merged.groupby('Date').cumcount(),
        price_trends = positions.set_index('Date') # Overall market for poato trading
```

```
# Compute summary statistics
max_price = price_trends.Price.max()
min_price = price_trends.Price.min()
max_date = price_trends.Price.idxmax()
min_date = price_trends.Price.idxmin()

print("Max Price of {} occurs on {}".format(max_price, max_date))
print("Min Price of {} occurs on {}".format(min_price, min_date))

# Daily data is hard to draw a conlucsion on, weekly gives a better picture of the price
weekly = price_trends['Price'].resample('W').mean()
weekly.plot(grid = True, figsize=(10,10),title='Weekly avg prices')
plt.ylabel("Price")
```

```
Max Price of 1519.7 occurs on 2020-08-31 00:00:00
Min Price of 8.5 occurs on 2020-08-20 00:00:00
```

```
Out[9]: Text(0, 0.5, 'Price')
```



8 Are there any factors that can help predict potato prices?

Yes the attributes of the potato can be used to help predict potato prices, although, not very well. The highest correlation found is the colour of the skin. Which indicates this can be used to help predict pricing using a learning algorithim.

The maturity of the potato is very good indicator of the price. Potato prices have some of the highest prices, where the maturiy is shorter. Longer maturites tend to have a stable price. We can further build on this by categorzing the maturities and computing the corrleation between the price. This will help us assign weights to each maturity in order to compute the correlation Because of time constratints I will leave the excercise for future enhancements.

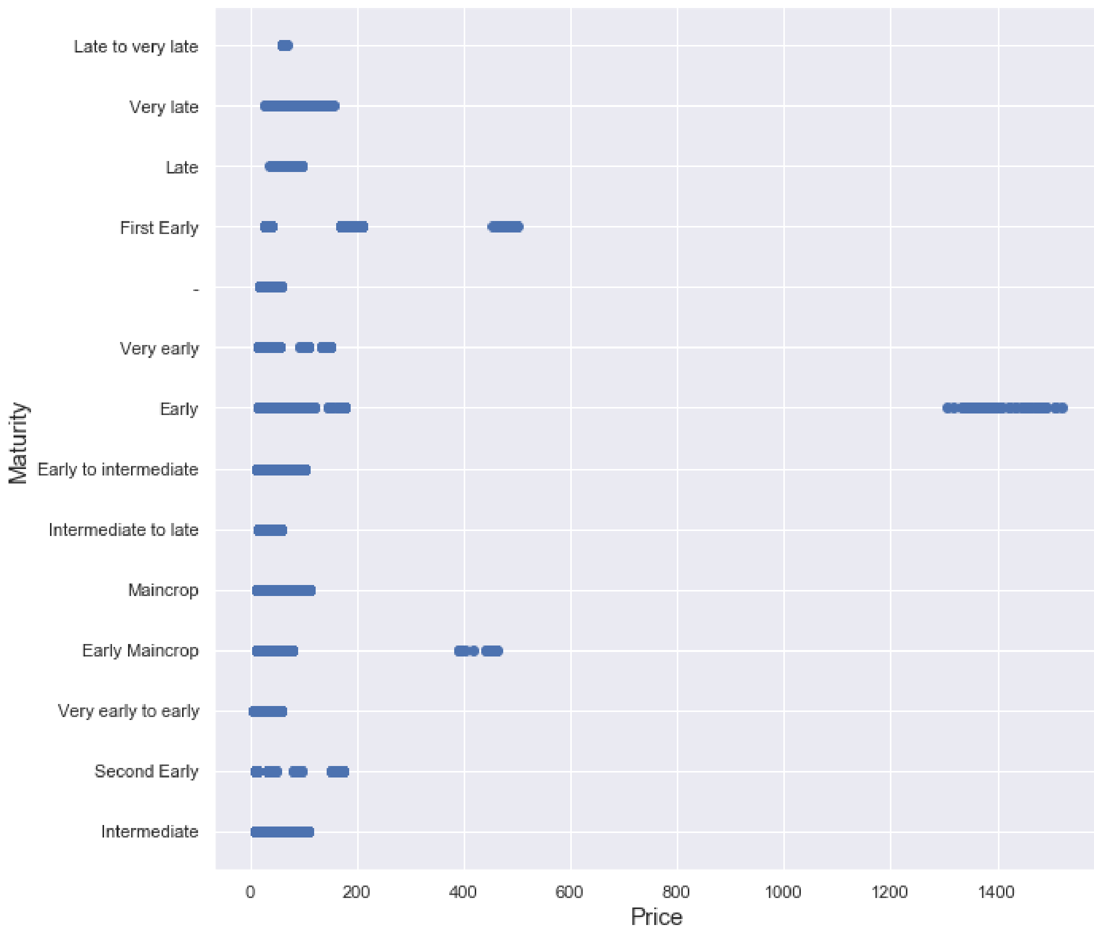
Below I have the correlation matrix for the attributes of the potato. I categorized the caolumns using the built-in method, this method is sometimes not efficient, becuase the weights are arbitrary. This method provides a good estimate in understanding the data.

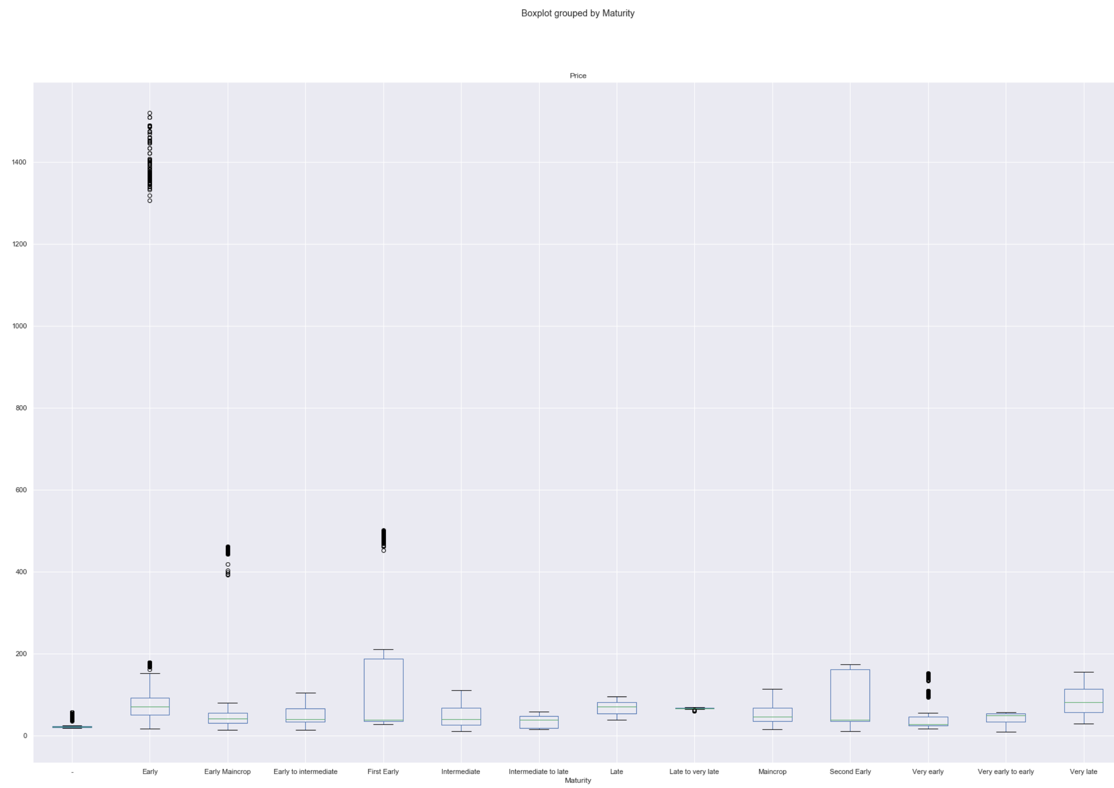
```
In [73]: potato_prices = positions.merge(potato_info, on='Product ID')
         plt.figure(figsize = (10,10))
         plt.xlabel('Price', fontsize=15)
         plt.ylabel('Maturity', fontsize=15)
         plt.scatter(potato_prices['Price'], potato_prices['Maturity'])
         sns.despine
         potato_prices.boxplot('Price','Maturity')

         categorize_prices = potato_prices.copy()
         categorize_prices['Colour of skin']= categorize_prices['Colour of skin'].astype('catego
         categorize_prices['Country']= categorize_prices['Country'].astype('category').cat.codes
         categorize_prices['Shape of tuber']= categorize_prices['Shape of tuber'].astype('catego
         categorize_prices['Colour of base of lightsprout']= categorize_prices['Colour of base o
         categorize_prices['Variety Name']= categorize_prices['Variety Name'].astype('category')
         categorize_prices['Colour of base of lightsprout']= categorize_prices['Depth of eyes'].
         categorize_prices['Height of plants']= categorize_prices['Height of plants'].astype('ca
         categorize_prices['Frequency of berries']= categorize_prices['Frequency of berries'].as
         categorize_prices.corr()
```

```
Out[73]:                                Client ID  Product ID     Price  Variety Name  \
         Client ID                       1.000000   -0.074444 -0.003412     -0.075326
         Product ID                     -0.074444    1.000000  0.036308      0.999431
         Price                          -0.003412    0.036308  1.000000      0.035340
         Variety Name                   -0.075326    0.999431  0.035340      1.000000
         Country                         0.018168    0.134160 -0.042057      0.136839
         Shape of tuber                  0.031648   -0.100794 -0.041551     -0.096012
         Colour of skin                 -0.040825    0.109408  0.164066      0.103298
         Colour of base of lightsprout  -0.027587    0.108555  0.091351      0.105588
         Height of plants                0.034261    0.267695  0.031578      0.273255
         Frequency of berries           -0.000672   -0.162083 -0.121572     -0.155670

                                         Country  Shape of tuber  Colour of skin  \
         Client ID                      0.018168        0.031648       -0.040825
         Product ID                     0.134160       -0.100794        0.109408
         Price                         -0.042057       -0.041551        0.164066
         Variety Name                   0.136839       -0.096012        0.103298
         Country                        1.000000       -0.065473        0.052011
         Shape of tuber                -0.065473        1.000000       -0.040371
         Colour of skin                 0.052011       -0.040371        1.000000
         Colour of base of lightsprout  0.058634        0.039825        0.138018
         Height of plants               0.235765       -0.054195        0.107843
         Frequency of berries           0.217766        0.045332       -0.218283

                                        Colour of base of lightsprout  \
         Client ID                                          -0.027587
```

Product ID	0.108555
Price	0.091351
Variety Name	0.105588
Country	0.058634
Shape of tuber	0.039825
Colour of skin	0.138018
Colour of base of lightsprout	1.000000
Height of plants	-0.022613
Frequency of berries	-0.024054

	Height of plants	Frequency of berries
Client ID	0.034261	-0.000672
Product ID	0.267695	-0.162083
Price	0.031578	-0.121572
Variety Name	0.273255	-0.155670
Country	0.235765	0.217766
Shape of tuber	-0.054195	0.045332
Colour of skin	0.107843	-0.218283
Colour of base of lightsprout	-0.022613	-0.024054
Height of plants	1.000000	0.090708
Frequency of berries	0.090708	1.000000


Late to very late
Very late
Late
First Early
-
Very early
Early
Early to intermediate
Intermediate to late
Maincrop
Early Maincrop
Very early to early
Second Early
Intermediate
Maturity
0
200
400
600
800
1000
1200
1400
Price



9 Are there any factors that can help predict client activity?

A good indicator for client activity is their region, with a dominant portion of traders coming from clients in the midwest.

Another indicator for trading activity is the the industry where there is strong correlation between Industrial clients and trading activity.

Attributes from the potatoes can also predict the client activity. The most traded potato id can give a sense for future activity.

```
In [77]: print(positions_merged.groupby(['Client Location',])['Date'].count().sort_values(ascend
         print(positions_merged.groupby(['Client Type',])['Date'].count().sort_values(ascending=
         positions_merged.groupby(['Maturity'])['Date'].count().sort_values().head()
         positions_merged.groupby(['Product ID'])['Date'].count().sort_values().head()
```

```
Client Location
Midwest      13142
Northeast     6743
North         4038
West          1956
Name: Date, dtype: int64
Client Type
Industrial     19652
```

```
Organic        2316
Hydroponitc    2238
Traditional    1673
Name: Date, dtype: int64
```

```
Out[77]: Product ID
         20      9
         284    12
         6      13
         280    23
         130    25
         Name: Date, dtype: int64
```

10 Summarize what has happened during this period

During this period the activity and prices are their lowest in May and peak in June.

Summer months appear to be where the highest activity and prices occur for this product type.

The fact that activity and pricing is consistent is intitutive. One would reason, that as market interest increases for a particular product, the price will be driven higher.

Potato prices movements are generally in line with each other, following similar trends and have a high correlation between product ids.

Client market control is heavily favored by clients coming from the Industrial sector in the Midwest region. We can use this to help predict pricing as we know where the activity and potato pricing lies.

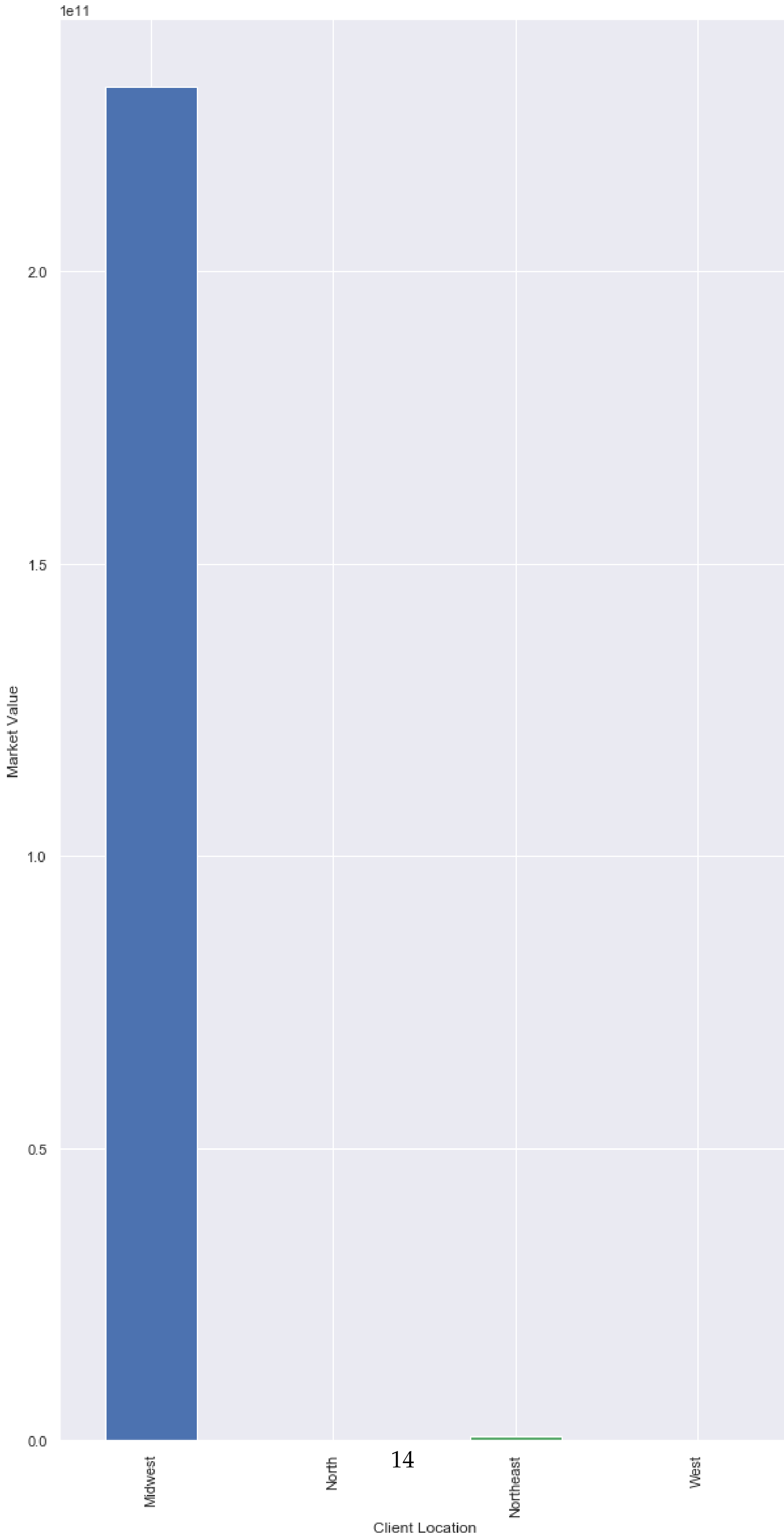
10.0.1 We see majority of the market value is controlled by those located in the Midwest.

10.0.2 The next largest is the Northeast but is pale in comparison,

```
In [42]: region_sum = positions_merged.groupby('Client Location')['Market Value'].sum()
         print(region_sum.apply(lambda x: '{0:.2f}'.format(x)))


         region_sum_plt = region_sum.plot(kind='bar',figsize=(10,20))
         region_sum_plt.set_ylabel('Market Value')
```

```
Client Location
Midwest      231650623218.59
North           127527663.01
Northeast       764053837.21
West             95691518.80
Name: Market Value, dtype: object
```

```
Out[42]: Text(0, 0.5, 'Market Value')
```

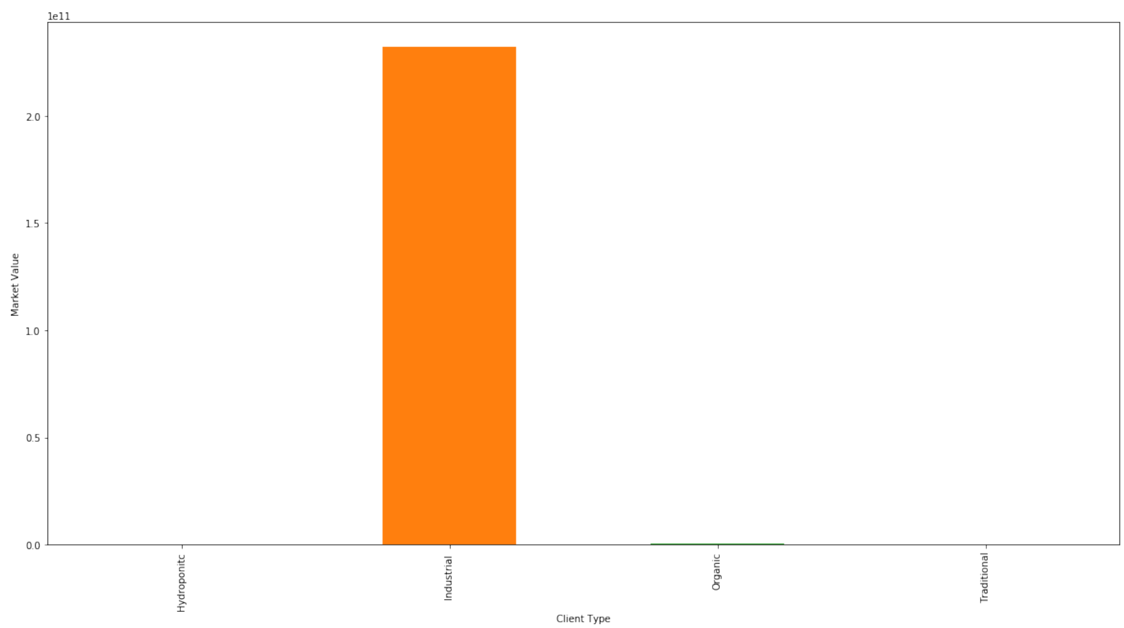

1e11
2.0
1.5
1.0
0.5
0.0
Market Value
Midwest
North
Northeast
West
Client Location

10.0.3 Majortiy of the market share is controlled by clients in the Industrial field

```
In [8]: industry_sum = positions_merged.groupby('Client Type')['Market Value'].sum()
        print(industry_sum.apply(lambda x: '{0:.2f}'.format(x)))
        industry_sum.plot(kind='bar', figsize=(20,10))
        plt.ylabel('Market Value')
```

```
Client Type
Hydroponitc        54930213.16
Industrial     232056014860.38
Organic           441874498.27
Traditional        85076665.81
Name: Market Value, dtype: object
```

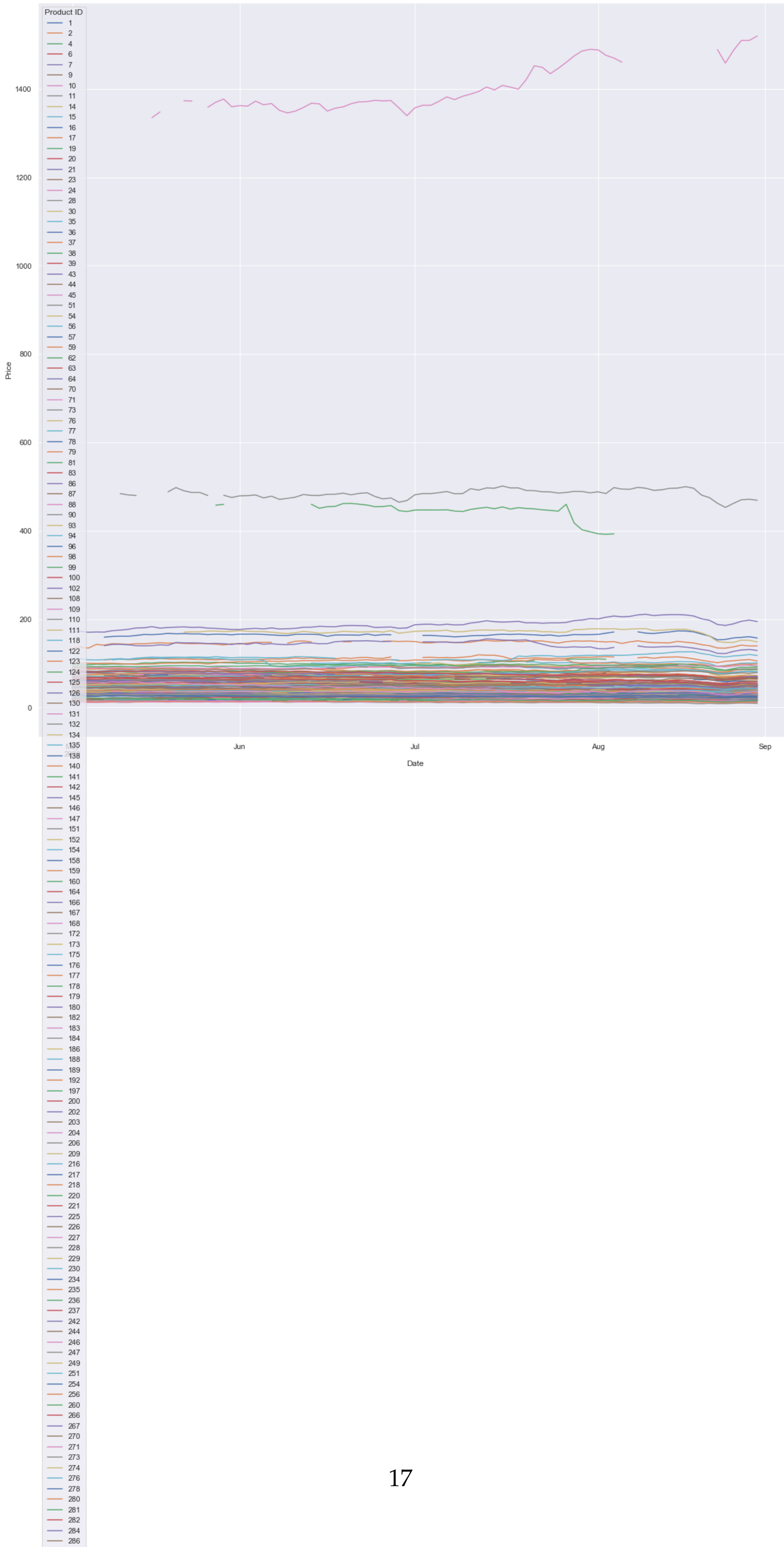
```
Out[8]: Text(0, 0.5, 'Market Value')
```



Pricing between products are highly correlated and follow similar trend throughout this time period.

```
In [44]: pivoted = pd.pivot_table(price_trends, values='Price', columns='Product ID', index='Dat
         pivoted.idxmax(1).to_frame().T

         pivoted.plot(grid = True, figsize=(20,20))
         plt.ylabel("Price")
         #print(pivoted.corr())
```

```
Out[44]: Text(0, 0.5, 'Price')
```


Product ID
1
2
4
6
7
9
10
11
14
15
16
17
19
20
21
23
24
28
30
35
36
37
38
39
43
44
45
51
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246
247
249
251
254
256
260
266
267
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271
273
274
276
278
280
281
282
284
286
288
1400
1200
1000
800
600
400
200
0
Price
Jun
Jul
Aug
Sep
Date