Week 6 - Clustering - Python

October 24, 2018

1 Data Warehousing and Data Mining

1.1 Labs

1.1.1 Prepared by Gilroy Gordon

Contact Information SCIT ext. 3643
ggordonutech@gmail.com
gilroy.gordon@utech.edu.jm

1.1.2 Week 6 - Clustering in Python

Additional Reference Resources:
http://scikit-learn.org/stable/modules/clustering.html

1.2 Objectives

```
> Data Preprocessing
     > Missing Values (Na and nulls)
> Data Mining
     > Clustering (Kmeans)
> Visualizations
     > Elbow method (Within Cluster Sum of Squares)
> Discussion on how to proceed
```

1.3 Aim: Am I able to segment groups based on

1.4 Import required libraries and acquire data

```
In [1]: # import required libraries
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline
```

```
In [2]: data_path = './data/credit-card-data.csv' # Path to data file
        data = pd.read_csv(data_path)
        data.head(15)
```

```
Out[2]:    cust_id      balance  balance_frequency  purchases  oneoff_purchases  \
        0   C10001    40.900749           0.818182      95.40              0.00
        1   C10002  3202.467416           0.909091       0.00              0.00
        2   C10003  2495.148862           1.000000     773.17            773.17
        3   C10004  1666.670542           0.636364    1499.00           1499.00
        4   C10005   817.714335           1.000000      16.00             16.00
        5   C10006  1809.828751           1.000000    1333.28              0.00
        6   C10007   627.260806           1.000000    7091.01           6402.63
        7   C10008  1823.652743           1.000000     436.20              0.00
        8   C10009  1014.926473           1.000000     861.49            661.49
        9   C10010   152.225975           0.545455    1281.60           1281.60
        10  C10011  1293.124939           1.000000     920.12              0.00
        11  C10012   630.794744           0.818182    1492.18           1492.18
        12  C10013  1516.928620           1.000000    3217.99           2500.23
        13  C10014   921.693369           1.000000    2137.93            419.96
        14  C10015  2772.772734           1.000000       0.00              0.00

            installments_purchases  cash_advance  purchases_frequency  \
        0                    95.40      0.000000             0.166667
        1                     0.00   6442.945483             0.000000
        2                     0.00      0.000000             1.000000
        3                     0.00    205.788017             0.083333
        4                     0.00      0.000000             0.083333
        5                  1333.28      0.000000             0.666667
        6                   688.38      0.000000             1.000000
        7                   436.20      0.000000             1.000000
        8                   200.00      0.000000             0.333333
        9                     0.00      0.000000             0.166667
        10                  920.12      0.000000             1.000000
        11                    0.00      0.000000             0.250000
        12                  717.76      0.000000             1.000000
        13                 1717.97      0.000000             0.750000
        14                    0.00    346.811390             0.000000

            oneoff_purchases_frequency  purchases_installments_frequency  \
        0                     0.000000                          0.083333
        1                     0.000000                          0.000000
        2                     1.000000                          0.000000
        3                     0.083333                          0.000000
        4                     0.083333                          0.000000
        5                     0.000000                          0.583333
        6                     1.000000                          1.000000
        7                     0.000000                          1.000000
        8                     0.083333                          0.250000
```

```
9                    0.166667                          0.000000
10                   0.000000                          1.000000
11                   0.250000                          0.000000
12                   0.250000                          0.916667
13                   0.166667                          0.750000
14                   0.000000                          0.000000

    cash_advance_frequency  cash_advance_trx  purchases_trx  credit_limit  \
0                 0.000000                 0              2          1000
1                 0.250000                 4              0          7000
2                 0.000000                 0             12          7500
3                 0.083333                 1              1          7500
4                 0.000000                 0              1          1200
5                 0.000000                 0              8          1800
6                 0.000000                 0             64         13500
7                 0.000000                 0             12          2300
8                 0.000000                 0              5          7000
9                 0.000000                 0              3         11000
10                0.000000                 0             12          1200
11                0.000000                 0              6          2000
12                0.000000                 0             26          3000
13                0.000000                 0             26          7500
14                0.083333                 1              0          3000

       payments  minimum_payments  prc_full_payment  tenure
0    201.802084        139.509787          0.000000      12
1   4103.032597       1072.340217          0.222222      12
2    622.066742        627.284787          0.000000      12
3      0.000000               NaN          0.000000      12
4    678.334763        244.791237          0.000000      12
5   1400.057770       2407.246035          0.000000      12
6   6354.314328        198.065894          1.000000      12
7    679.065082        532.033990          0.000000      12
8    688.278568        311.963409          0.000000      12
9   1164.770591        100.302262          0.000000      12
10  1083.301007       2172.697765          0.000000      12
11   705.618627        155.549069          0.000000      12
12   608.263689        490.207013          0.250000      12
13  1655.891435        251.137986          0.083333      12
14   805.647974        989.962866          0.000000      12
```

In [3]:
```
# What columns are in the data set ? Do they have spaces that I should consider
data.columns
```

Out[3]:
```
Index(['cust_id', 'balance', 'balance_frequency', 'purchases',
       'oneoff_purchases', 'installments_purchases', 'cash_advance',
       'purchases_frequency', 'oneoff_purchases_frequency',
       'purchases_installments_frequency', 'cash_advance_frequency',
```

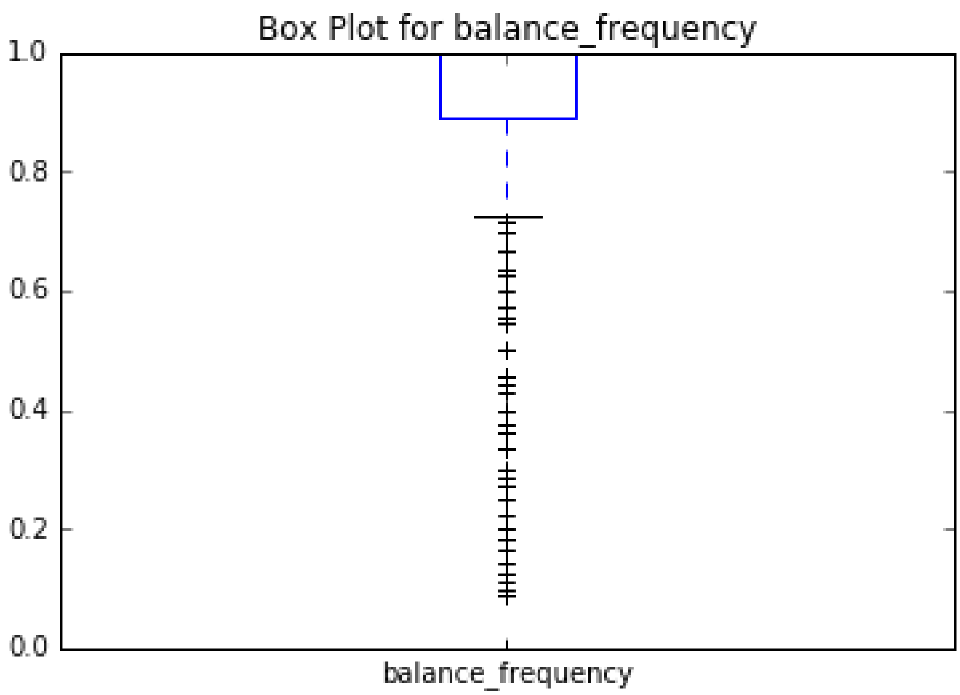
```
       'cash_advance_trx', 'purchases_trx', 'credit_limit', 'payments',
       'minimum_payments', 'prc_full_payment', 'tenure'],
      dtype='object')
```

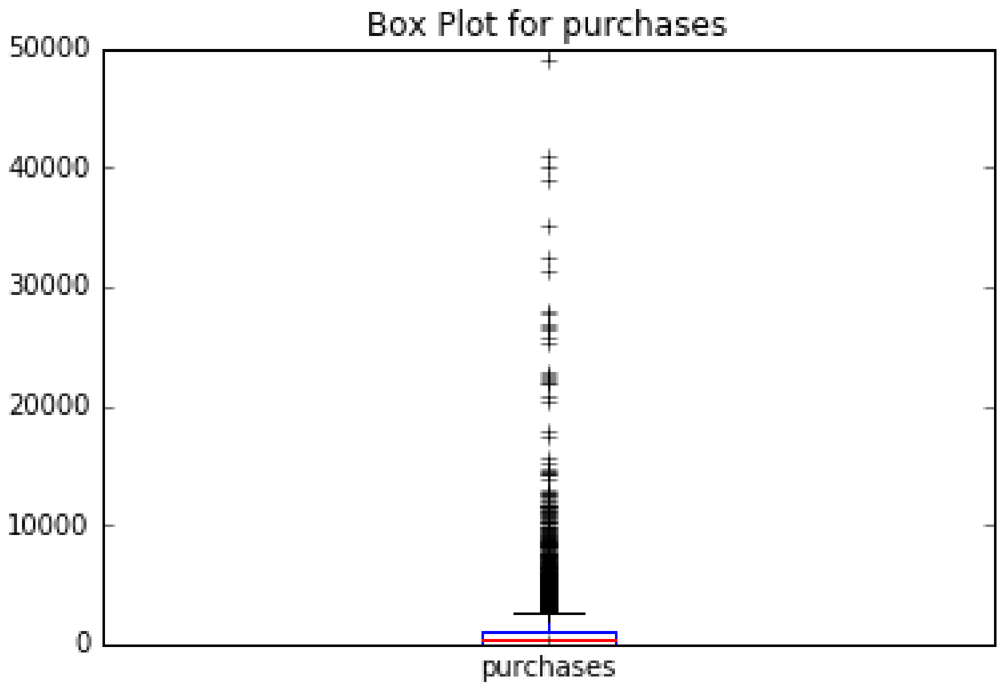
In [5]:
```
data.describe()
```

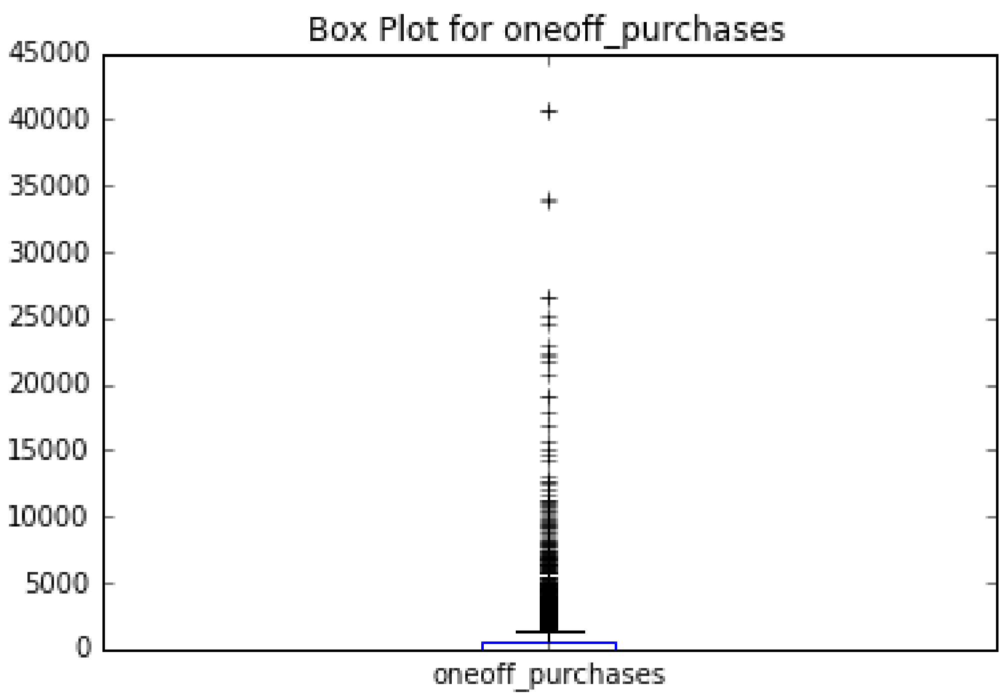
Out[5]:
```
            balance  balance_frequency     purchases  oneoff_purchases  \
count   8950.000000        8950.000000   8950.000000       8950.000000
mean    1564.474828           0.877271   1003.204834        592.437371
std     2081.531879           0.236904   2136.634782       1659.887917
min        0.000000           0.000000      0.000000          0.000000
25%      128.281915           0.888889     39.635000          0.000000
50%      873.385231           1.000000    361.280000         38.000000
75%     2054.140036           1.000000   1110.130000        577.405000
max    19043.138560           1.000000  49039.570000      40761.250000

       installments_purchases  cash_advance  purchases_frequency  \
count             8950.000000   8950.000000          8950.000000
mean               411.067645    978.871112             0.490351
std                904.338115   2097.163877             0.401371
min                  0.000000      0.000000             0.000000
25%                  0.000000      0.000000             0.083333
50%                 89.000000      0.000000             0.500000
75%                468.637500   1113.821139             0.916667
max              22500.000000  47137.211760             1.000000

       oneoff_purchases_frequency  purchases_installments_frequency  \
count                 8950.000000                       8950.000000
mean                     0.202458                          0.364437
std                      0.298336                          0.397448
min                      0.000000                          0.000000
25%                      0.000000                          0.000000
50%                      0.083333                          0.166667
75%                      0.300000                          0.750000
max                      1.000000                          1.000000

       cash_advance_frequency  cash_advance_trx  purchases_trx  credit_limit  \
count             8950.000000       8950.000000    8950.000000   8949.000000
mean                 0.135144          3.248827      14.709832   4494.449450
std                  0.200121          6.824647      24.857649   3638.815725
min                  0.000000          0.000000       0.000000     50.000000
25%                  0.000000          0.000000       1.000000   1600.000000
50%                  0.000000          0.000000       7.000000   3000.000000
75%                  0.222222          4.000000      17.000000   6500.000000
max                  1.500000        123.000000     358.000000  30000.000000

           payments  minimum_payments  prc_full_payment       tenure
count   8950.000000       8637.000000       8950.000000  8950.000000
```

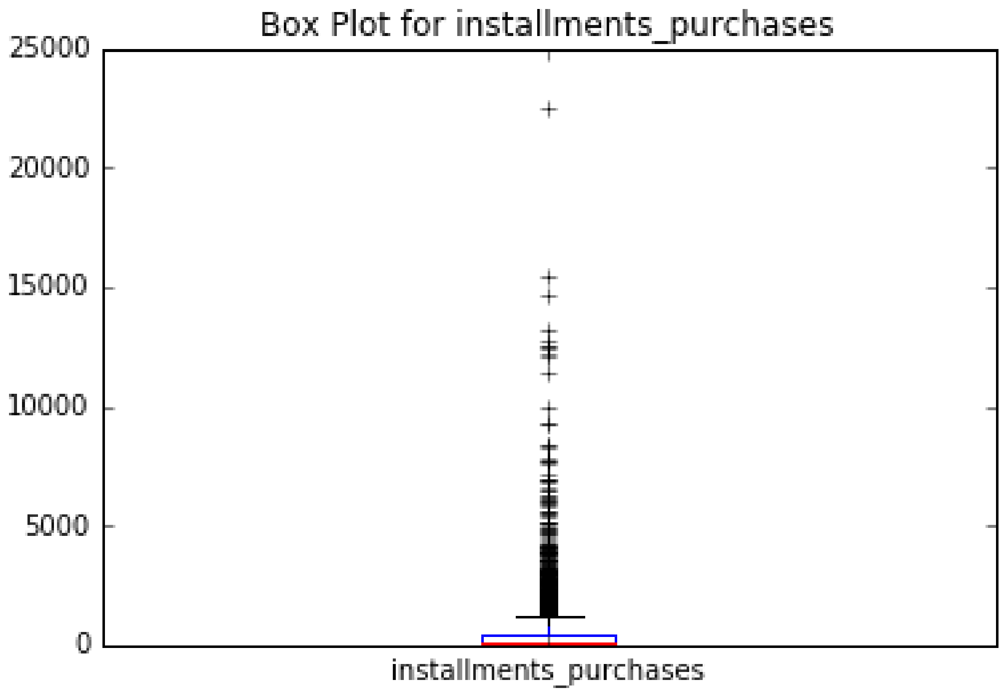
mean	1733.143852	864.206542	0.153715	11.517318
std	2895.063757	2372.446607	0.292499	1.338331
min	0.000000	0.019163	0.000000	6.000000
25%	383.276166	169.123707	0.000000	12.000000
50%	856.901546	312.343947	0.000000	12.000000
75%	1901.134317	825.485459	0.142857	12.000000
max	50721.483360	76406.207520	1.000000	12.000000

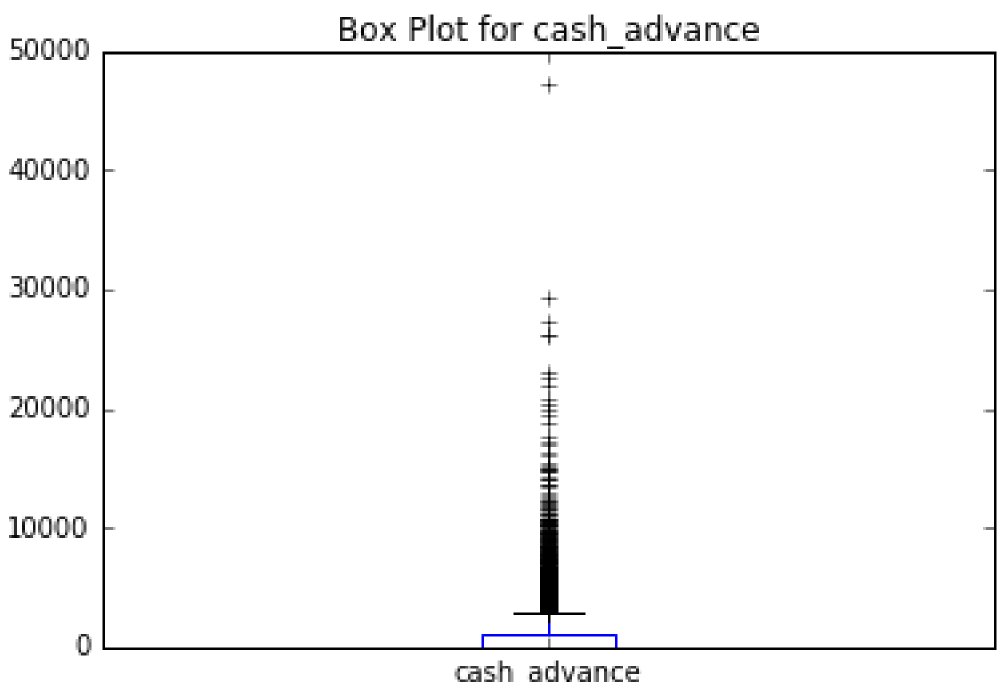
In [6]:
```
# Let's view the distribution of the data, where is it possible to find groups?
# We are using boxplots of all the columns except the first (cust_id which is a string)
for col in data.columns[2:]:
    data[col].plot(kind='box')
    plt.title('Box Plot for '+col)
    plt.show()
```

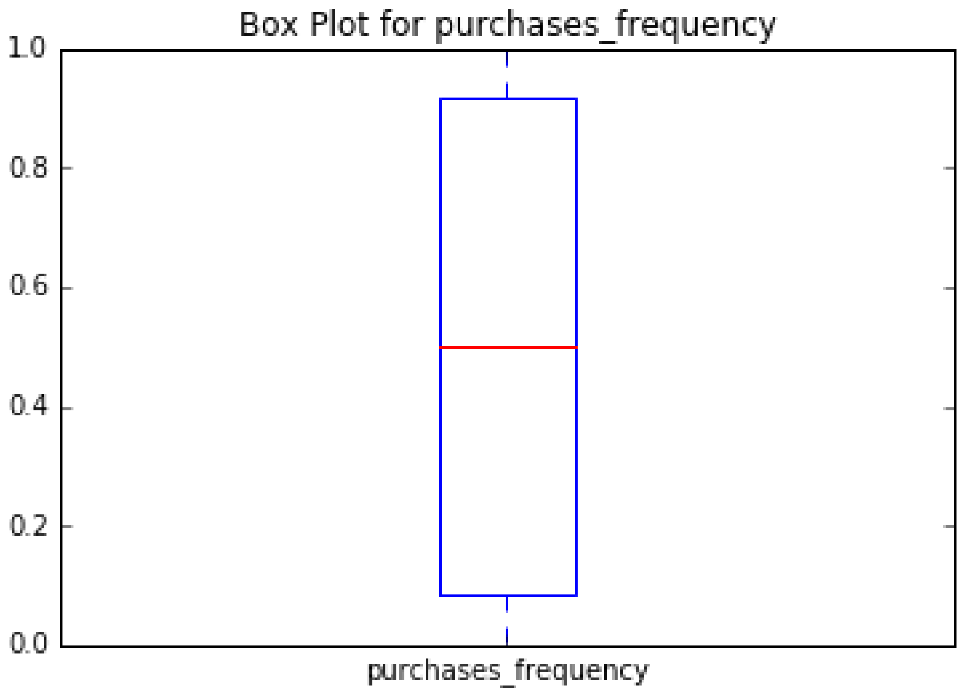


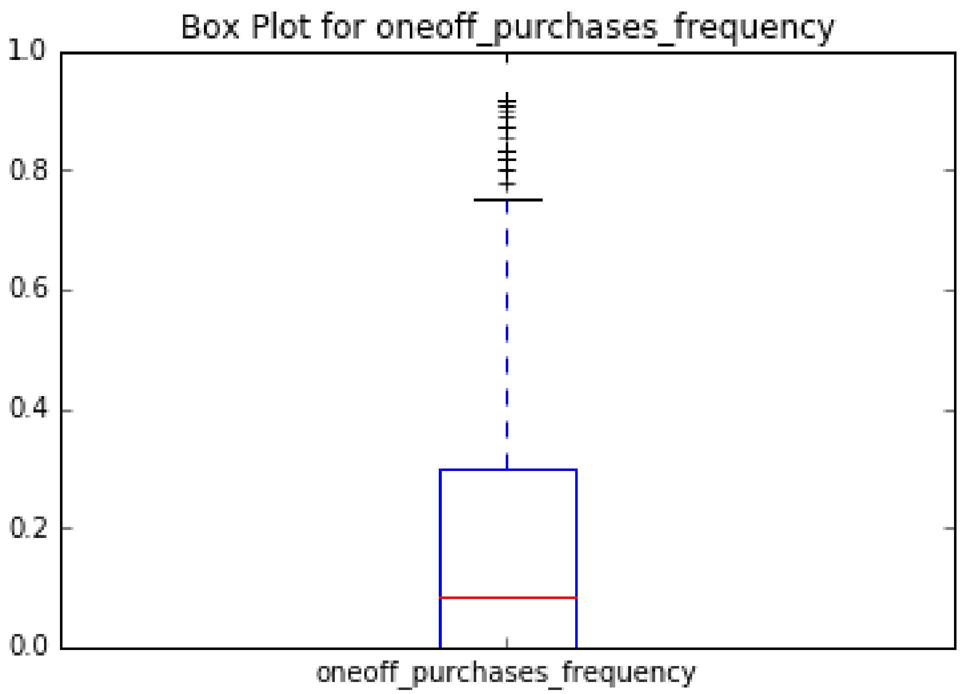

Box Plot for purchases
50000
40000
30000
20000
10000
0
purchases

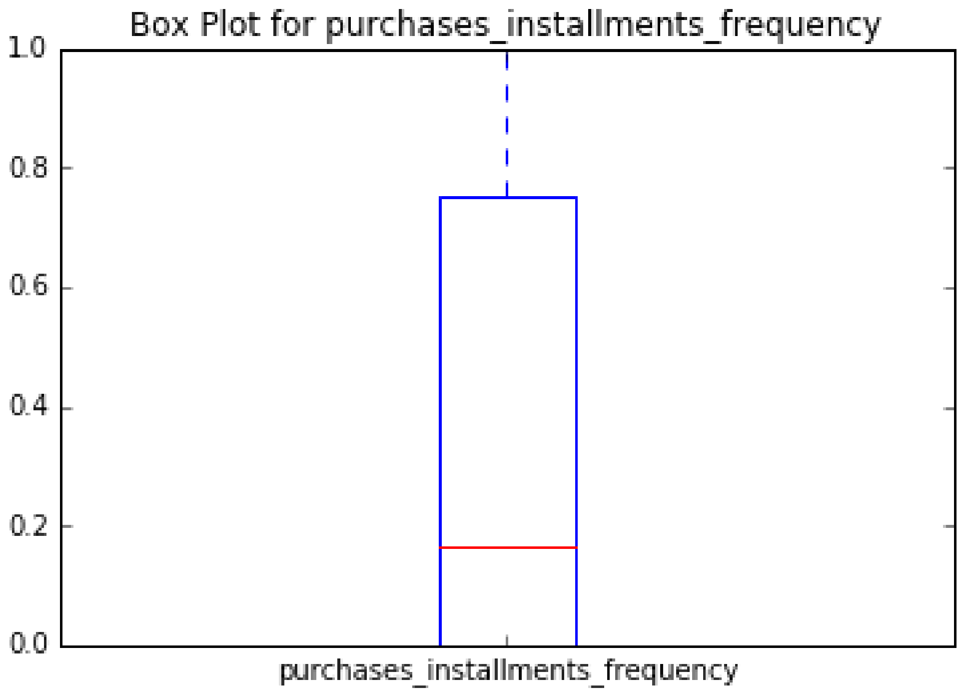

Box Plot for oneoff_purchases
45000
40000
35000
30000
25000
20000
15000
10000
5000
0
oneoff_purchases

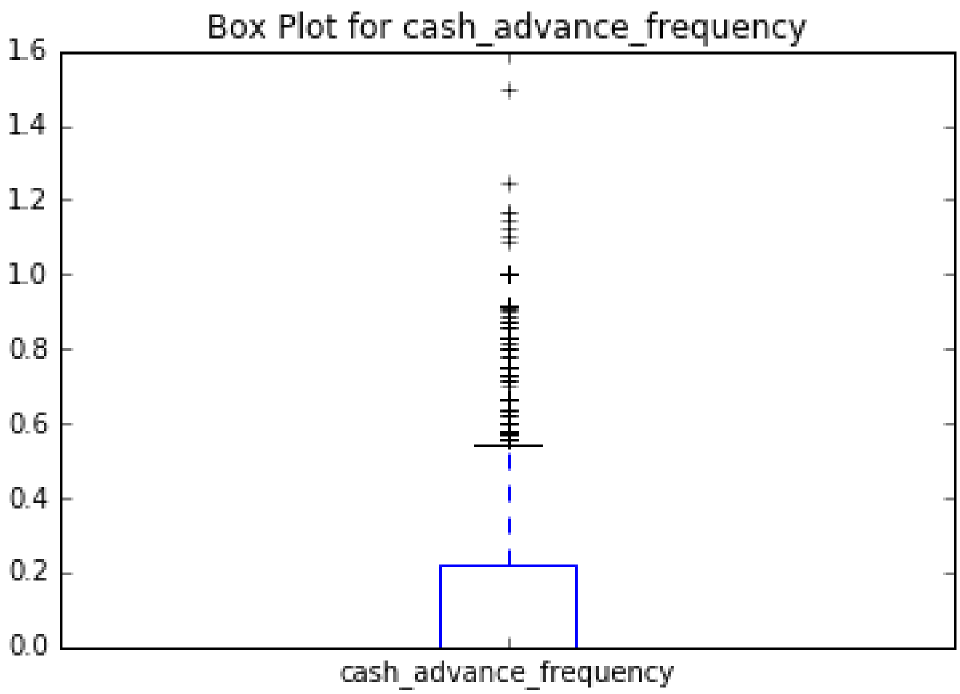

Box Plot for installments_purchases
25000
20000
15000
10000
5000
0
installments_purchases

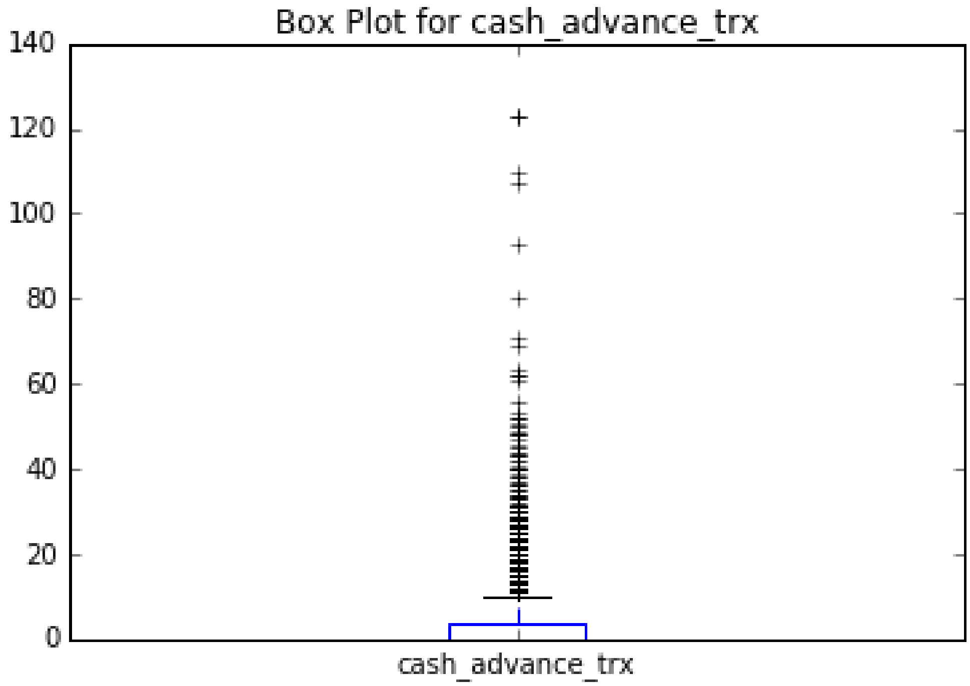

Box Plot for cash_advance
50000
40000
30000
20000
10000
0
cash_advance

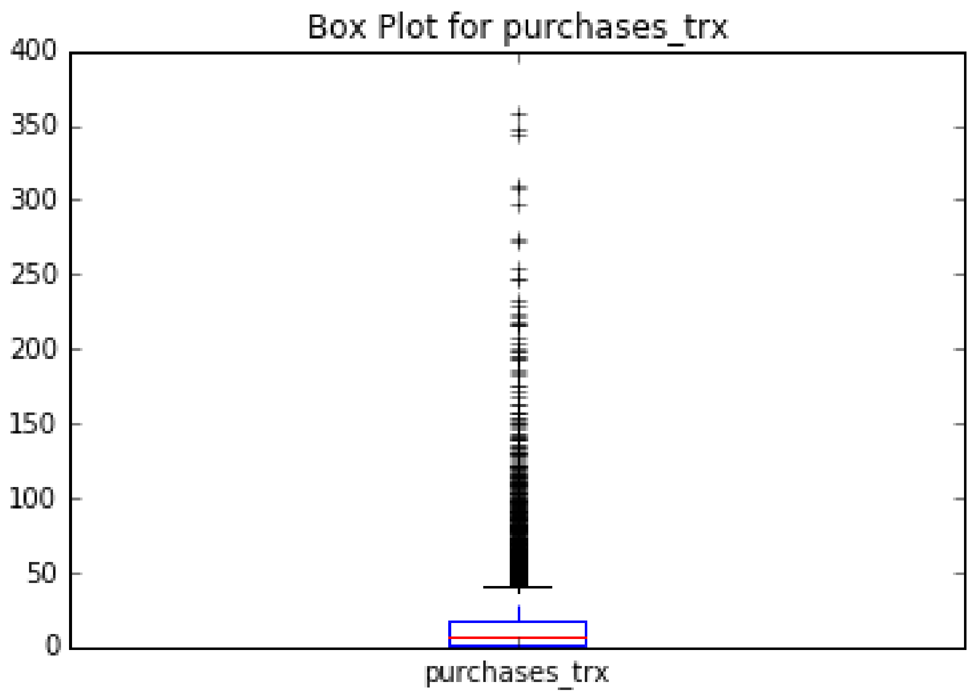

Box Plot for purchases_frequency
1.0
0.8
0.6
0.4
0.2
0.0
purchases_frequency

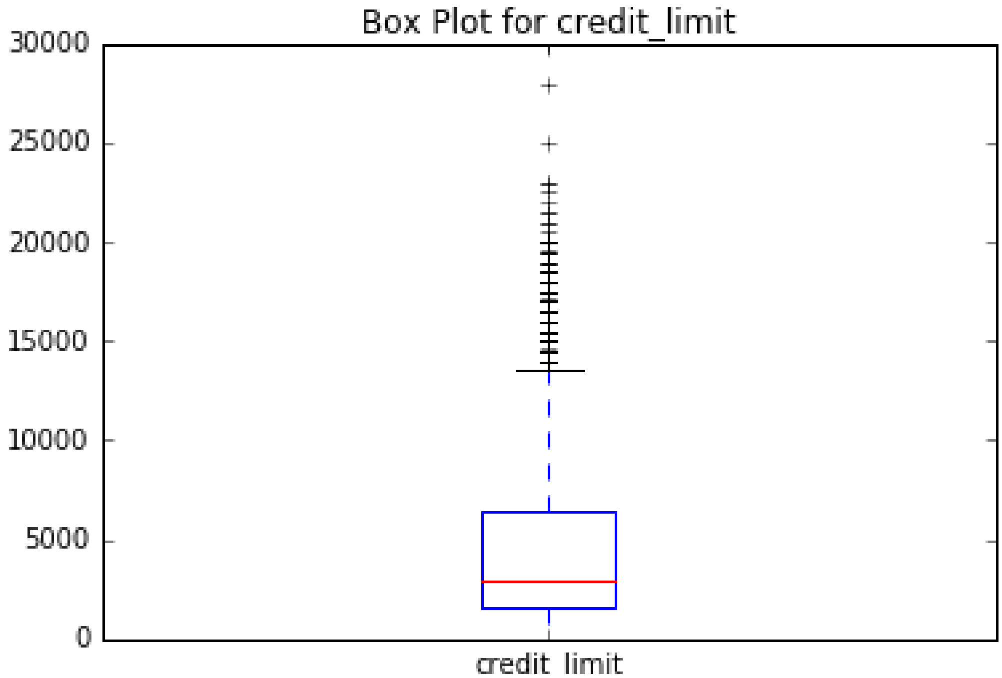

Box Plot for oneoff_purchases_frequency
1.0
0.8
0.6
0.4
0.2
0.0
oneoff_purchases_frequency

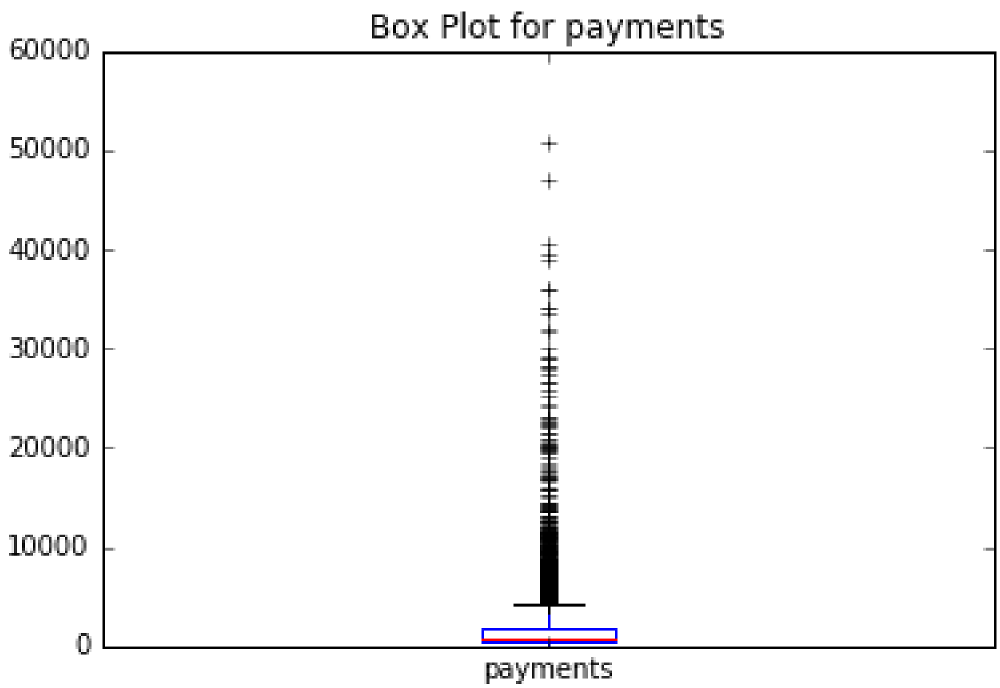

Box Plot for purchases_installments_frequency
1.0
0.8
0.6
0.4
0.2
0.0
purchases_installments_frequency

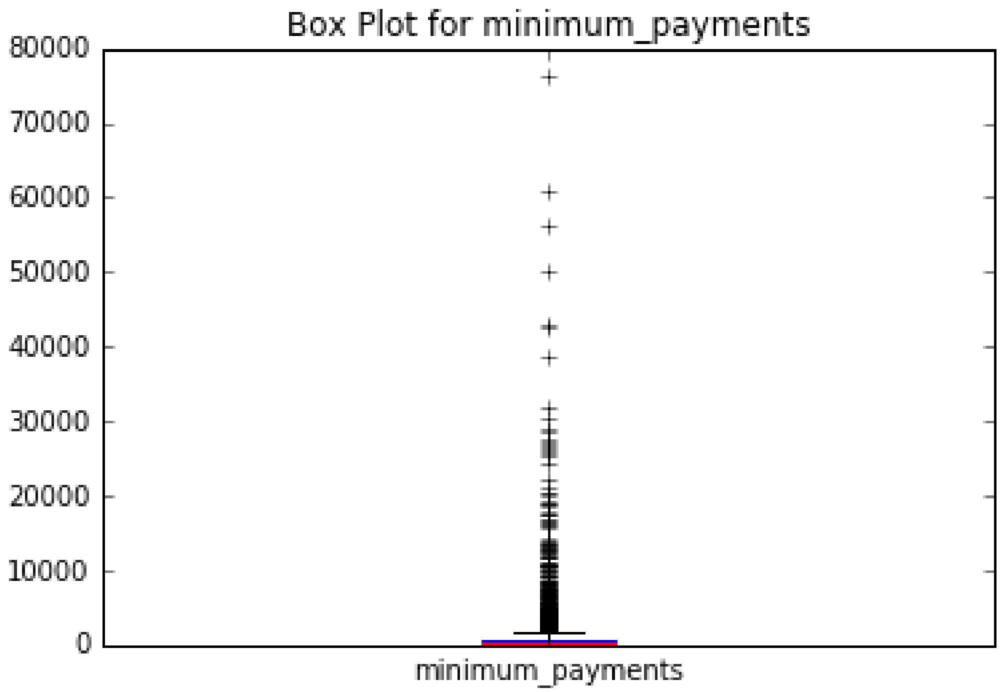

Box Plot for cash_advance_frequency
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
cash_advance_frequency

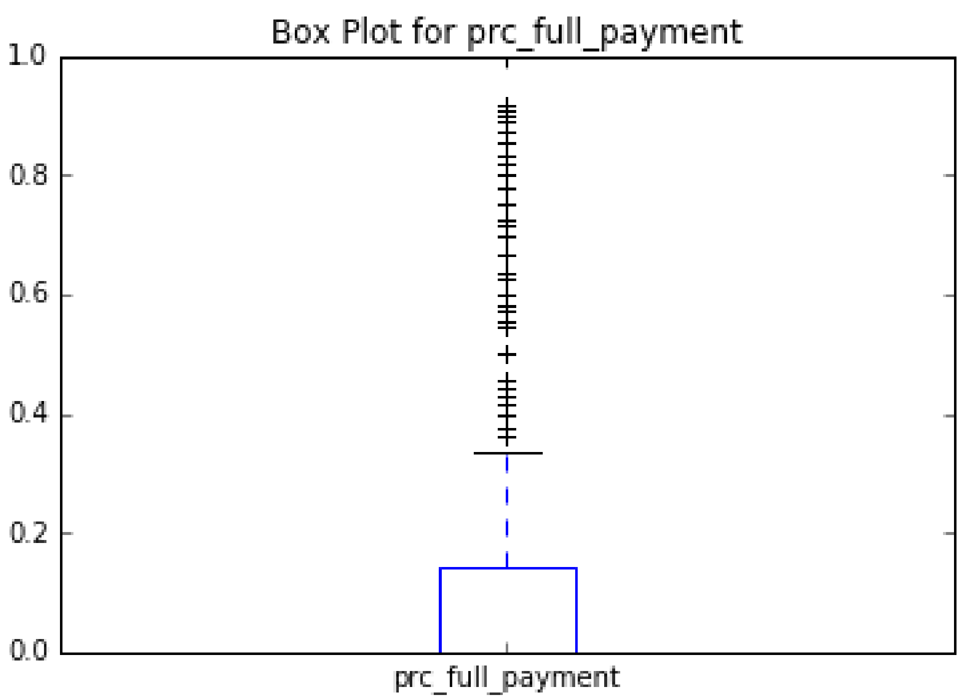

Box Plot for cash_advance_trx
140
120
100
80
60
40
20
0
cash_advance_trx

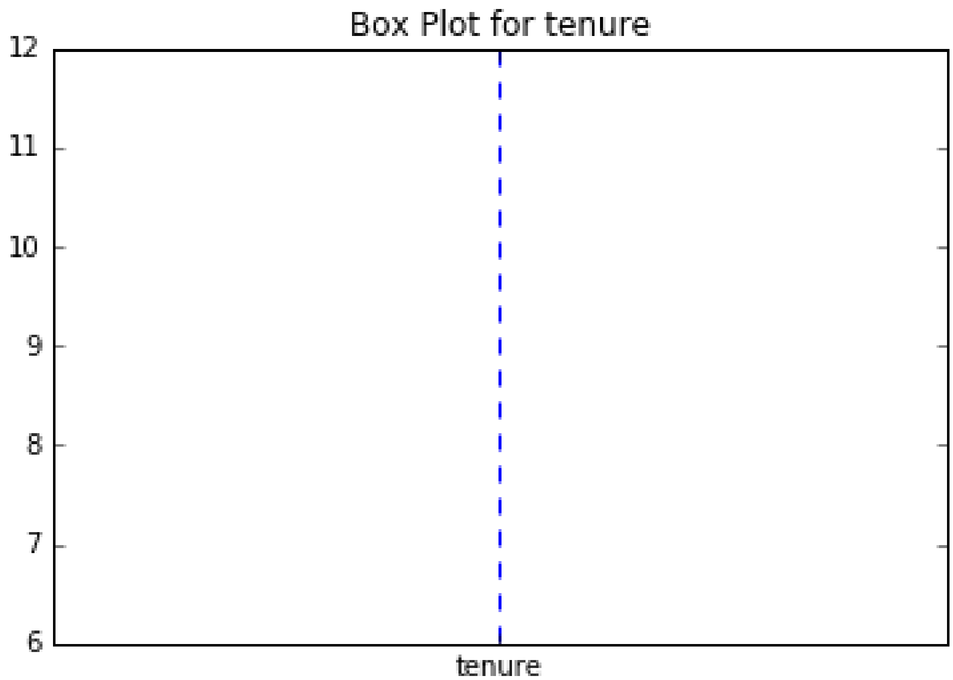

Box Plot for purchases_trx
400
350
300
250
200
150
100
50
0
purchases_trx


Box Plot for credit_limit
30000
25000
20000
15000
10000
5000
0
credit_limit


Box Plot for payments
60000
50000
40000
30000
20000
10000
0
payments


Box Plot for minimum_payments
80000
70000
60000
50000
40000
30000
20000
10000
0
minimum_payments


Box Plot for prc_full_payment
1.0
0.8
0.6
0.4
0.2
0.0
prc_full_payment



1.5 Aim: Can we identify groups based on purchases and payments?

If that is the case, we could offer different payment plans based on different purchases.

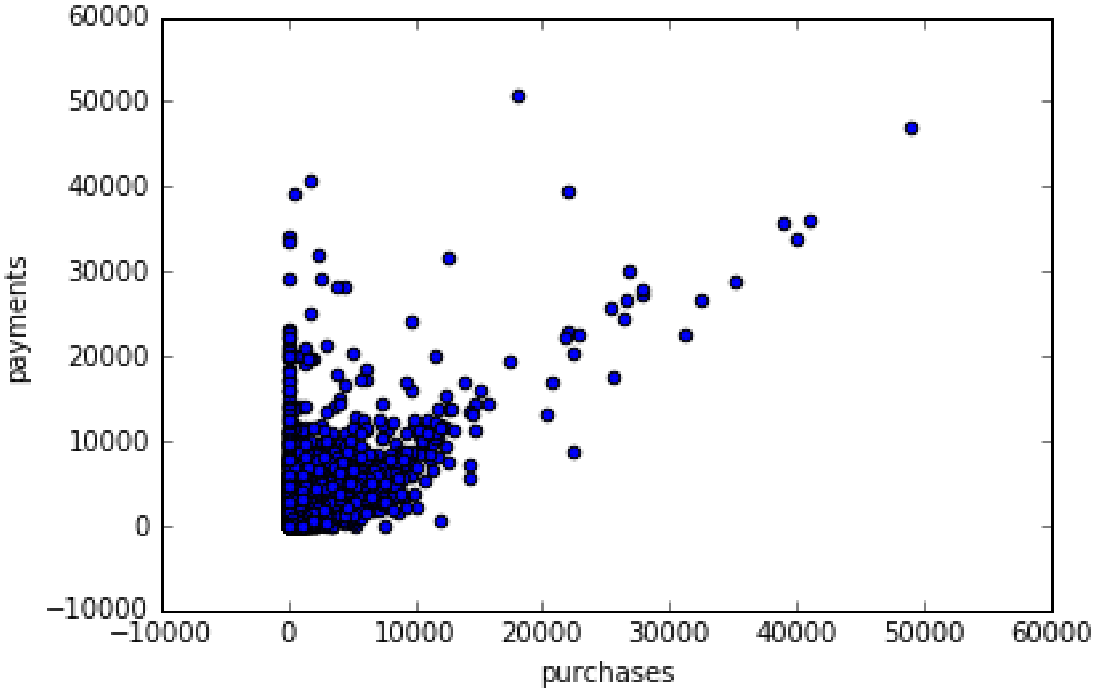
```
In [7]: cluster_data = data[['purchases','payments']]
        cluster_data.head()
```

Out[7]:

	purchases	payments
0	95.40	201.802084
1	0.00	4103.032597
2	773.17	622.066742
3	1499.00	0.000000
4	16.00	678.334763

```
In [8]: cluster_data.plot(kind='scatter',x='purchases',y='payments')
```

```
Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x7f836b17c4a8>
```



In [9]:
```
# Is there any missing data
missing_data_results = cluster_data.isnull().sum()
print(missing_data_results)

# perform imputation with median values
# not require since none missing
#cluster_data = cluster_data.fillna( data.median() )
```

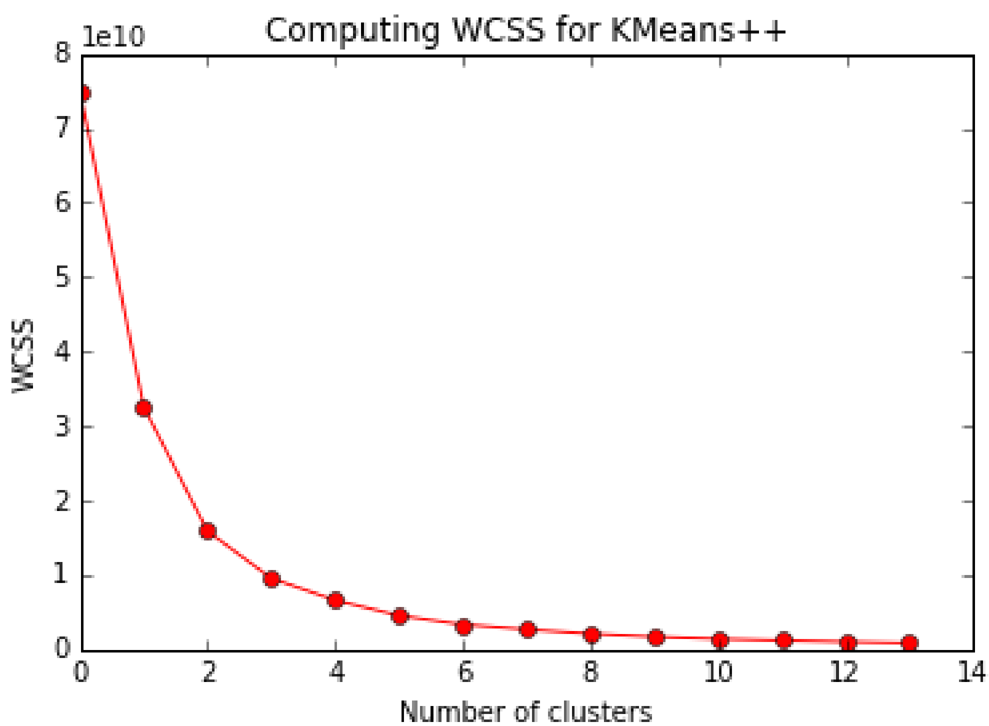
```
purchases    0
payments     0
dtype: int64
```

In [10]:
```
#retrieve just the values for all columns except customer id
data_values = cluster_data.iloc[ :, 1:].values
data_values
```

Out[10]:
```
array([[ 201.802084],
       [4103.032597],
       [ 622.066742],
       ...,
       [  81.270775],
       [  52.549959],
       [  63.165404]])
```

In [11]:
```
#import KMeans algorithm
from sklearn.cluster import KMeans
```

In [12]:
```
# Use the Elbow method to find a good number of clusters using WCSS (within-cluster sum
wcss = []
for i in range( 1, 15 ):
    kmeans = KMeans(n_clusters=i, init="k-means++", n_init=10, max_iter=300)
    kmeans.fit_predict( data_values )
    wcss.append( kmeans.inertia_ )

plt.plot( wcss, 'ro-', label="WCSS")
plt.title("Computing WCSS for KMeans++")
plt.xlabel("Number of clusters")
plt.ylabel("WCSS")
plt.show()
```



We're seeing an elbow at approx 3, so let's try 3 groups

In [13]:
```
kmeans = KMeans(n_clusters=3, init="k-means++", n_init=10, max_iter=300)
cluster_data["cluster"] = kmeans.fit_predict( data_values )
cluster_data
```

```
/usr/local/lib/python3.5/dist-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
```

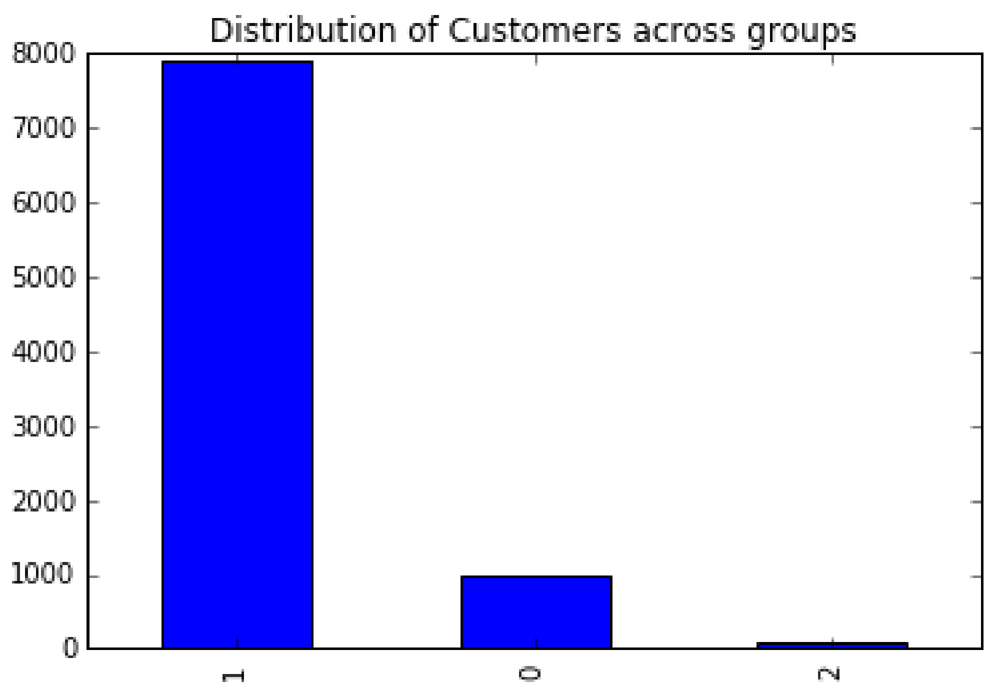
Out[13]:

	purchases	payments	cluster
0	95.40	201.802084	1
1	0.00	4103.032597	0
2	773.17	622.066742	1
3	1499.00	0.000000	1
4	16.00	678.334763	1
5	1333.28	1400.057770	1
6	7091.01	6354.314328	0
7	436.20	679.065082	1
8	861.49	688.278568	1
9	1281.60	1164.770591	1
10	920.12	1083.301007	1
11	1492.18	705.618627	1
12	3217.99	608.263689	1
13	2137.93	1655.891435	1
14	0.00	805.647974	1
15	1611.70	1993.439277	1
16	0.00	391.974562	1
17	519.00	254.590662	1
18	504.35	1720.837373	1
19	398.64	1053.980464	1
20	176.68	223.068600	1
21	6359.95	2077.959051	1
22	815.90	2359.629958	1
23	4248.35	9479.043842	0
24	0.00	1422.726707	1
25	399.60	215.306142	1
26	102.00	890.178845	1
27	233.28	207.773715	1
28	387.05	1601.448347	1
29	100.00	160.767773	1
...	...	...	...
8920	0.00	54.795084	1
8921	57.42	68.462579	1
8922	145.98	53.676054	1
8923	1898.88	669.039640	1
8924	74.00	214.921009	1
8925	418.59	422.538988	1
8926	580.00	641.303466	1
8927	315.20	231.274641	1
8928	500.00	456.745027	1
8929	0.00	0.000000	1
8930	84.00	124.373736	1

```
8931     235.80   189.090274        1
8932     180.00   138.203240        1
8933     619.60   106.138603        1
8934     110.50   161.476789        1
8935     465.90     0.000000        1
8936     712.50   605.716356        1
8937       0.00   117.738787        1
8938       0.00  1397.770131        1
8939     734.40    72.530037        1
8940     591.24   475.523262        1
8941     214.55   966.202912        1
8942     113.28    94.488828        1
8943      20.90    58.644883        1
8944    1012.73     0.000000        1
8945     291.12   325.594462        1
8946     300.00   275.861322        1
8947     144.40    81.270775        1
8948       0.00    52.549959        1
8949    1093.25    63.165404        1

[8950 rows x 3 columns]
```

In [24]:
```
cluster_data['cluster'].value_counts().plot(kind='bar',title='Distribution of Customers
```

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x7f83647e24a8>

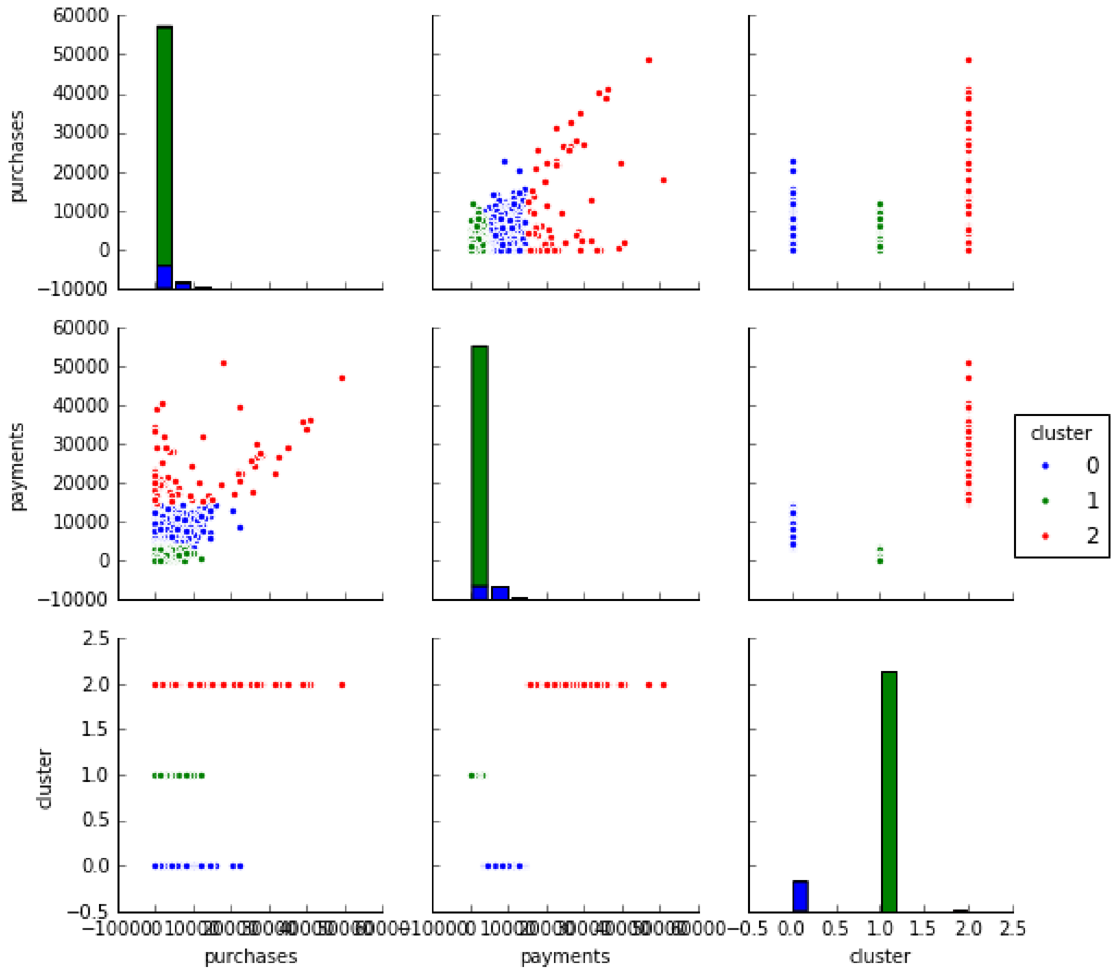


In [15]:

```
sns.pairplot( cluster_data, hue="cluster")
```

Out[15]:

```
<seaborn.axisgrid.PairGrid at 0x7f836dd89f98>
```



Looks nice, but what are we really seeing? Let's attempt to describe the groups

In [17]:

```
grouped_cluster_data = cluster_data.groupby('cluster')
grouped_cluster_data
```

Out[17]:

```
<pandas.core.groupby.DataFrameGroupBy object at 0x7f836531b128>
```

In [18]:

```
grouped_cluster_data.describe()
```

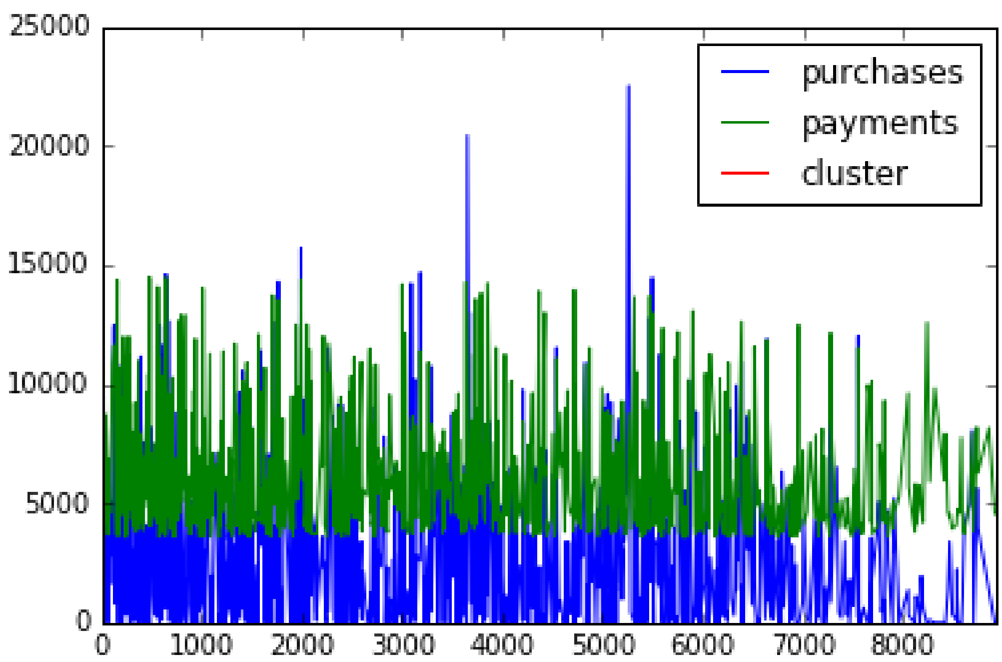
Out[18]:

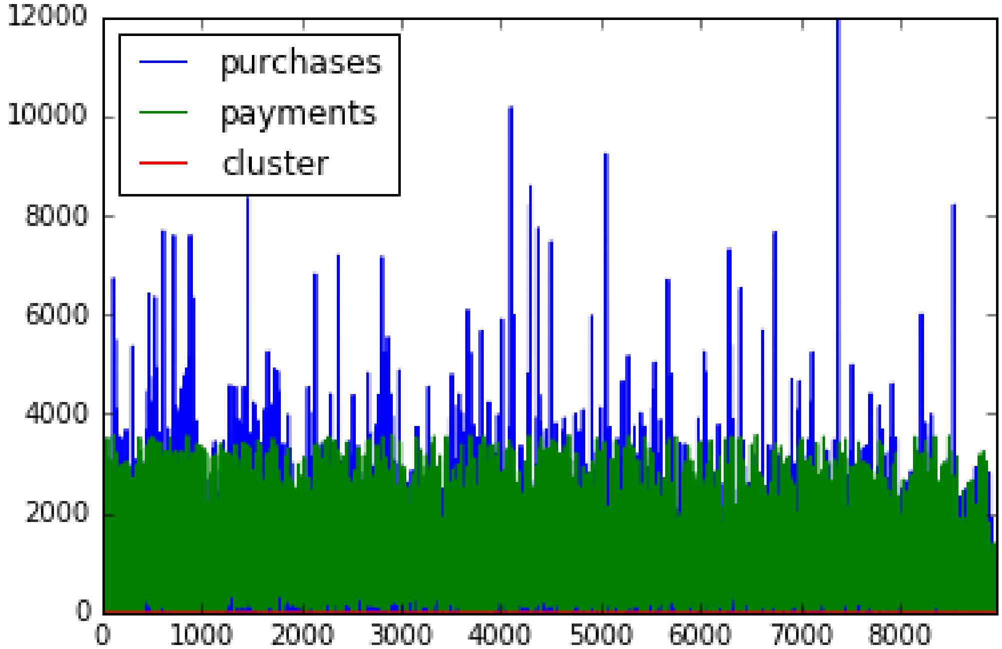
		purchases	payments	cluster
cluster				
0	count	977.000000	977.000000	977
	mean	2893.507165	6159.668584	0
	std	3248.509337	2505.563838	0

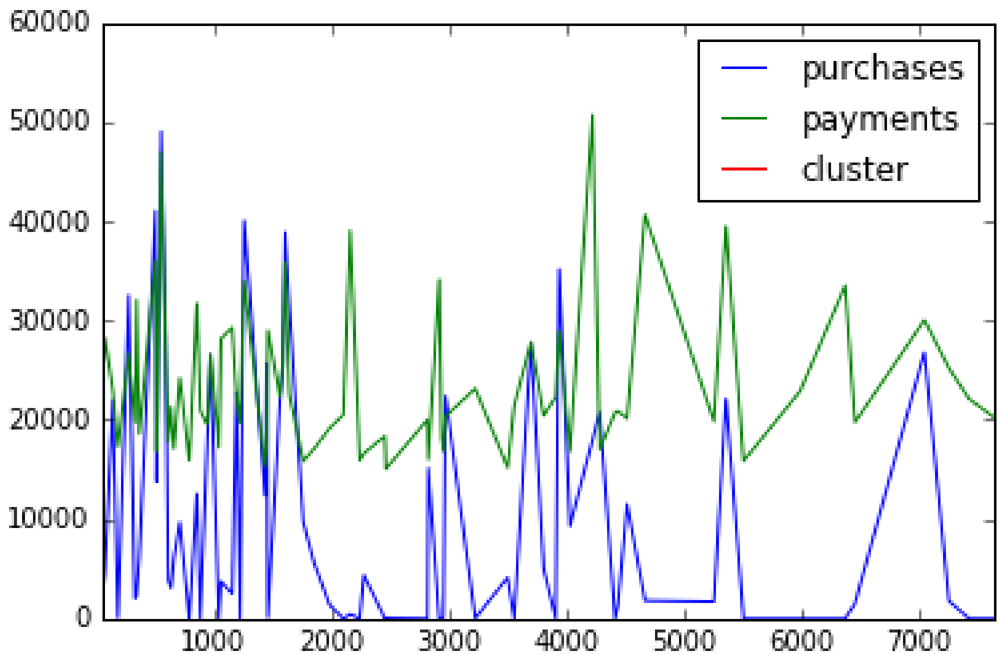
```
         min          0.000000    3569.182969        0
         25%        147.120000    4201.694496        0
         50%       1771.600000    5359.784024        0
         75%       4587.210000    7443.805810        0
         max      22500.000000   14481.465440        0
1        count     7899.000000    7899.000000     7899
         mean       680.066701     980.439425        1
         std        965.459756     829.030774        0
         min          0.000000       0.000000        1
         25%         35.000000     341.445479        1
         50%        324.000000     708.699641        1
         75%        924.645000    1411.360861        1
         max      11994.710000    3567.009988        1
2        count       74.000000      74.000000       74
         mean     10538.917432   23637.165609        2
         std      12900.044316    7698.746165        0
         min          0.000000   15043.665080        2
         25%         30.000000   17827.712822        2
         50%       3976.770000   20907.273725        2
         75%      21538.785000   27693.619535        2
         max      49039.570000   50721.483360        2
```

In [20]:
```
grouped_cluster_data.plot(subplots=True,)
```

Out[20]:
```
cluster
0    Axes(0.125,0.125;0.775x0.775)
1    Axes(0.125,0.125;0.775x0.775)
2    Axes(0.125,0.125;0.775x0.775)
dtype: object
```




purchases
payments
cluster
12000
10000
8000
6000
4000
2000
0
0
1000
2000
3000
4000
5000
6000
7000
8000


purchases
payments
cluster
60000
50000
40000
30000
20000
10000
0
1000
2000
3000
4000
5000
6000
7000

1.6 In - class assignment

1. Provide three(3) plots of the data to assist in describing the initial data set
2. Plot the differences between the groups above using at least two (2) charts.
3. Repeat the clustering activity on different columns in an attempt to provide additional marketing insight. If the results are not insightful state why