Week 6 - Clustering - Python

October 24, 2018

1 Data Warehousing and Data Mining

1.1 Labs

1.1.1 Prepared by Gilroy Gordon

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

In [53]:
```
data_path = './data/credit-card-data.csv' # Path to data file
data = pd.read_csv(data_path)
data.head(15)
```

Out[53]:

	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 [54]:
```
# What columns are in the data set ? Do they have spaces that I should consider
data.columns
```

Out[54]:
```
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 [55]:
```
data.describe()
```

Out[55]:

	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

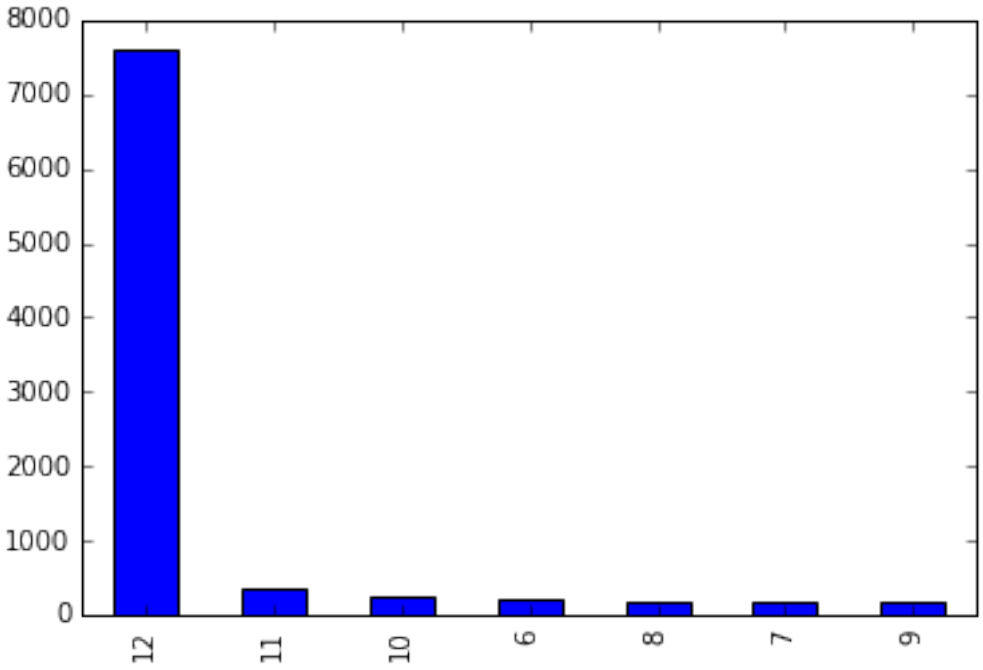
	cash_advance_frequency	cash_advance_trx	purchases_trx	credit_limit
count	8950.000000	8950.000000	8950.000000	8949.000000
mean	0.135144	3.248827	14.709832	4494.449450
std	0.200121	6.824647	24.857649	3638.815725
min	0.000000	0.000000	0.000000	50.000000
25%	0.000000	0.000000	1.000000	1600.000000
50%	0.000000	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

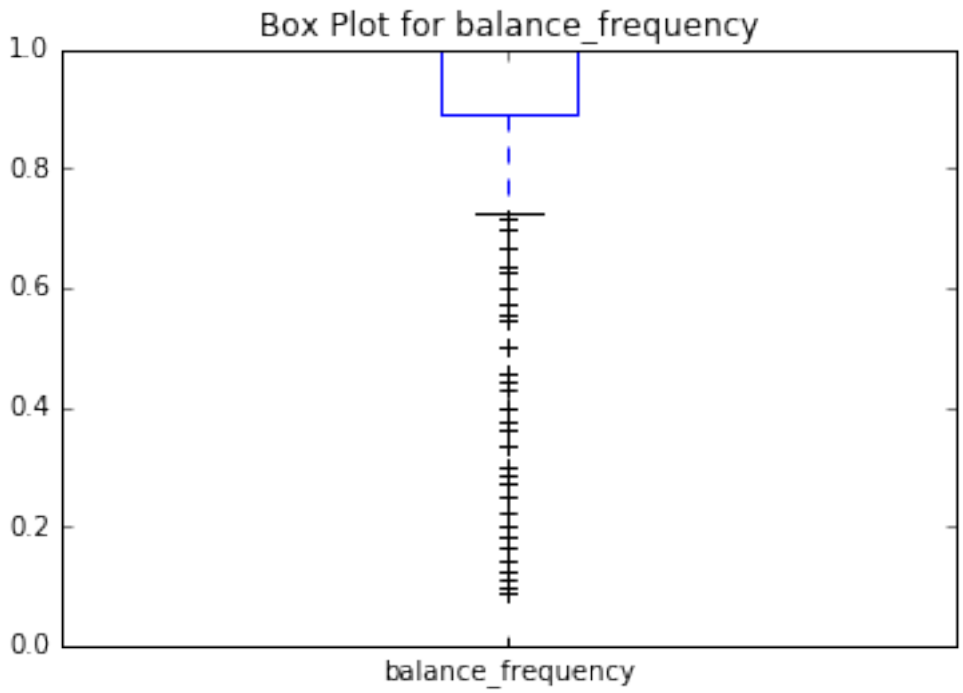
mean	1733.143852	864.206542	0.153715	11.517318
std	2895.063757	2372.446607	0.292499	1.338331
min	0.000000	0.019163	0.000000	6.000000
25%	383.276166	169.123707	0.000000	12.000000
50%	856.901546	312.343947	0.000000	12.000000
75%	1901.134317	825.485459	0.142857	12.000000
max	50721.483360	76406.207520	1.000000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

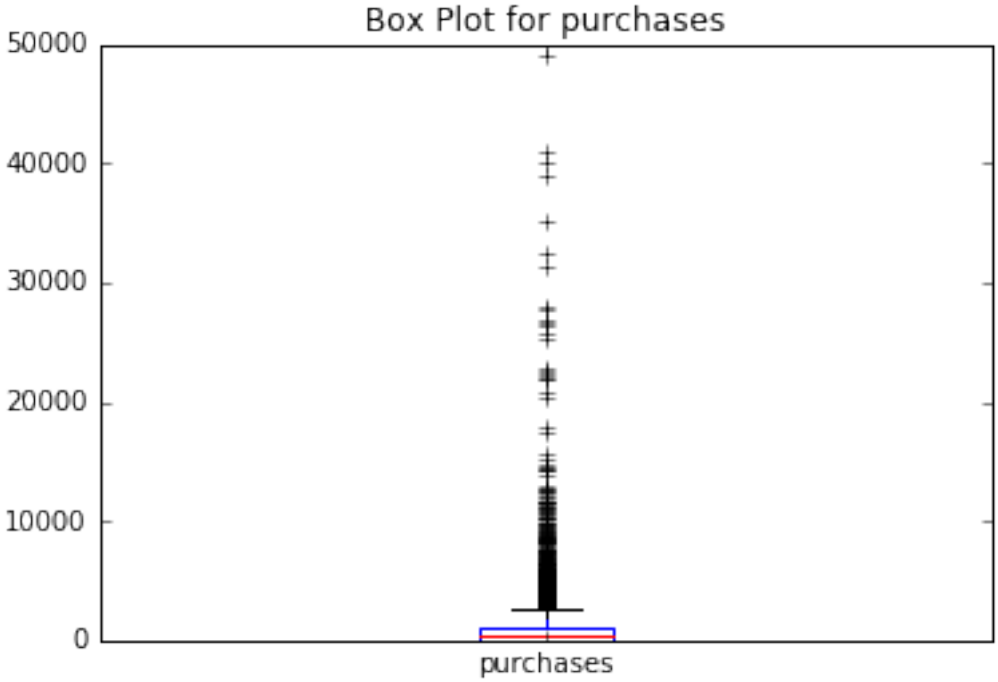
In [56]:
```
data['tenure'].value_counts().plot(kind='bar')
```

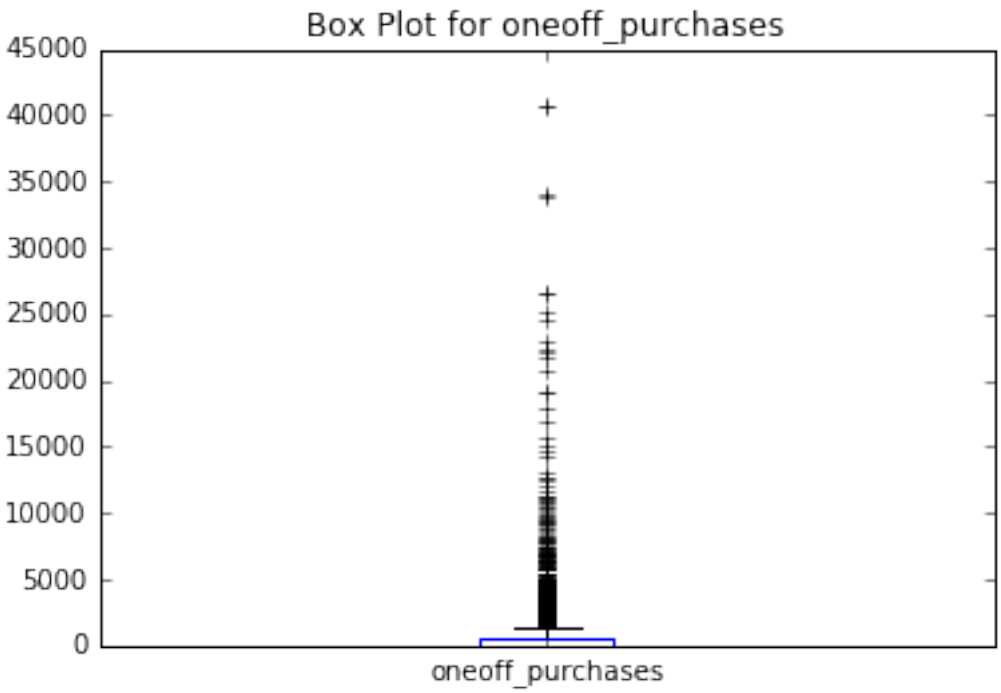
Out[56]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7e41fce908>

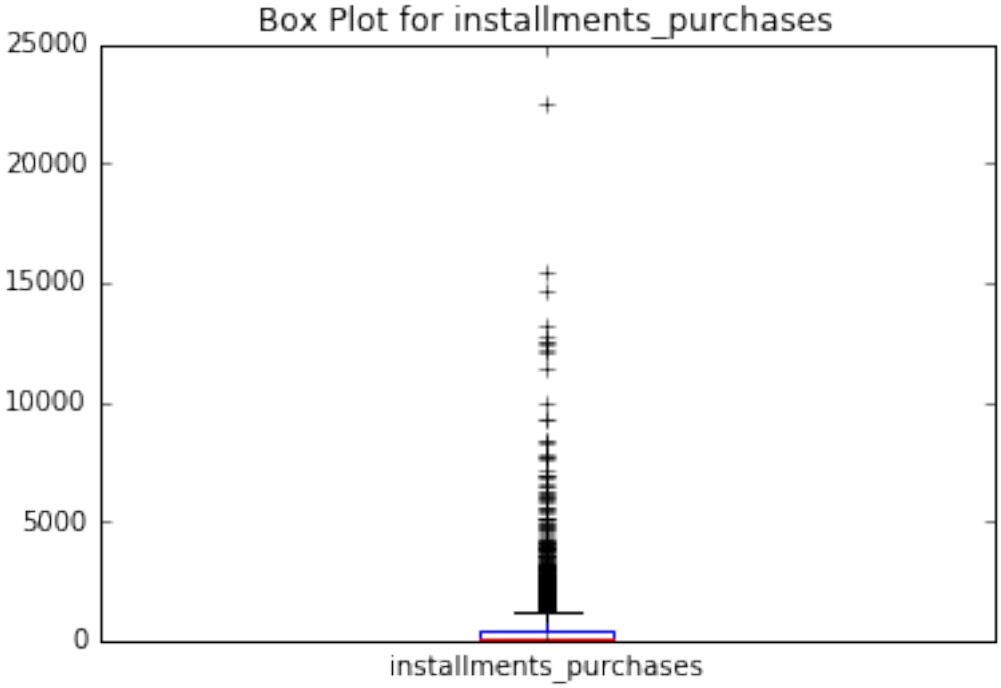


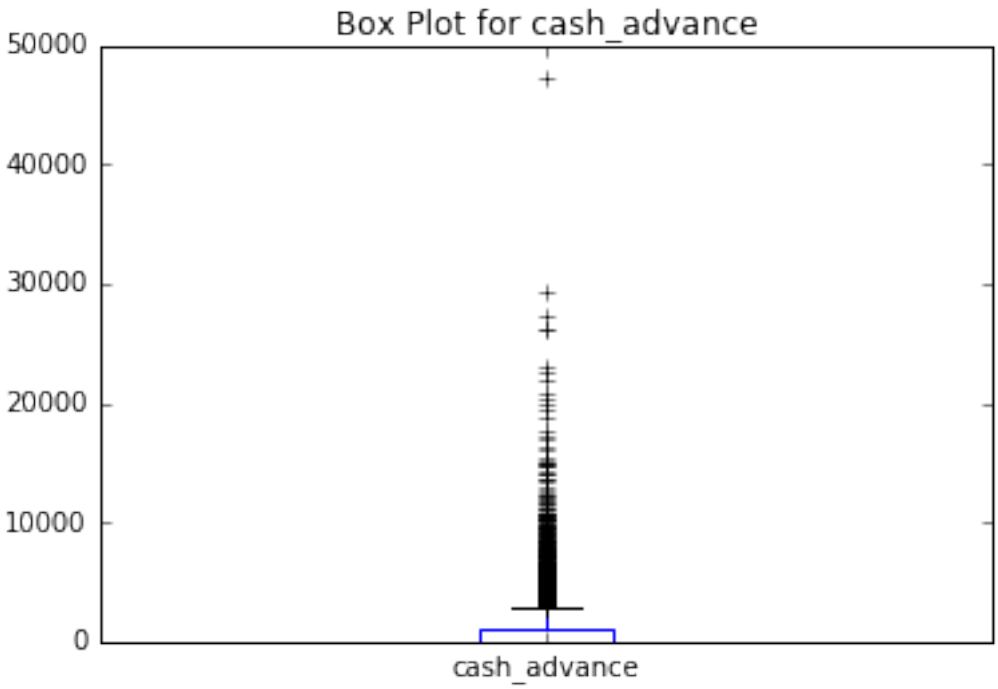
In [57]:
```
# Let's view the distribution of the data, where is it possible to find groups?
# We are using boxplots of all the columns except the first (cust_id which is a string)
for col in data.columns[2:]:
    data[col].plot(kind='box')
    plt.title('Box Plot for '+col)
    plt.show()
```

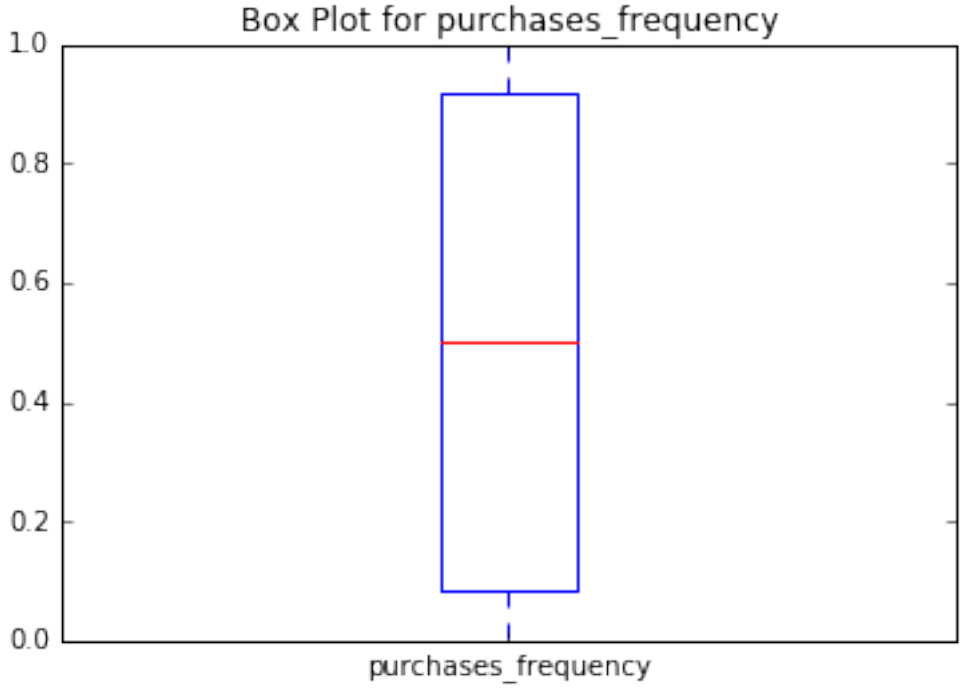

Box Plot for balance_frequency
1.0
0.8
0.6
0.4
0.2
0.0
balance_frequency

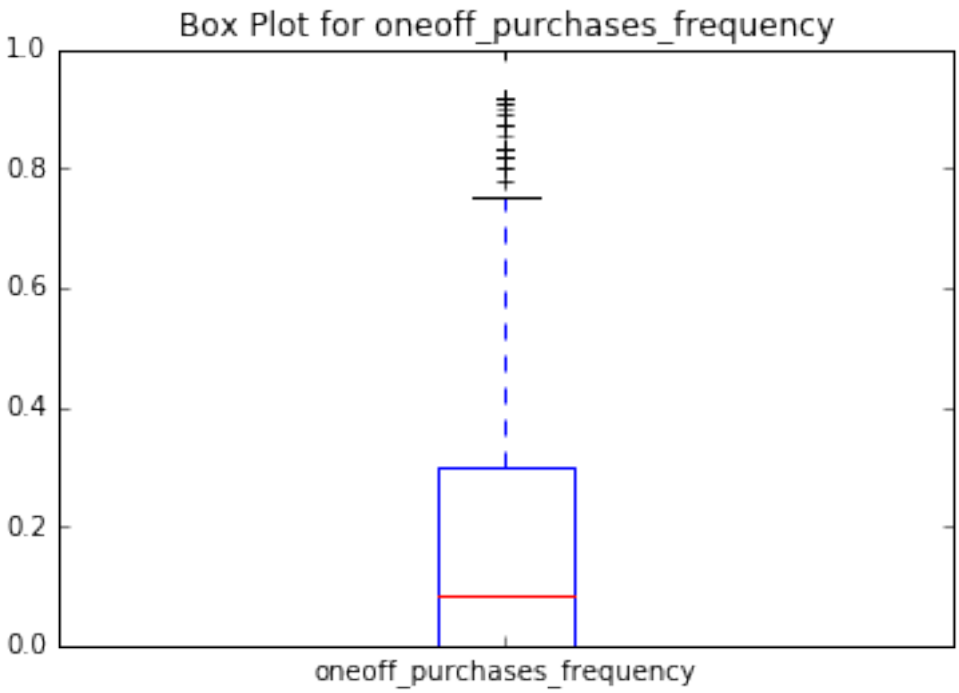

Box Plot for purchases
50000
40000
30000
20000
10000
0
purchases

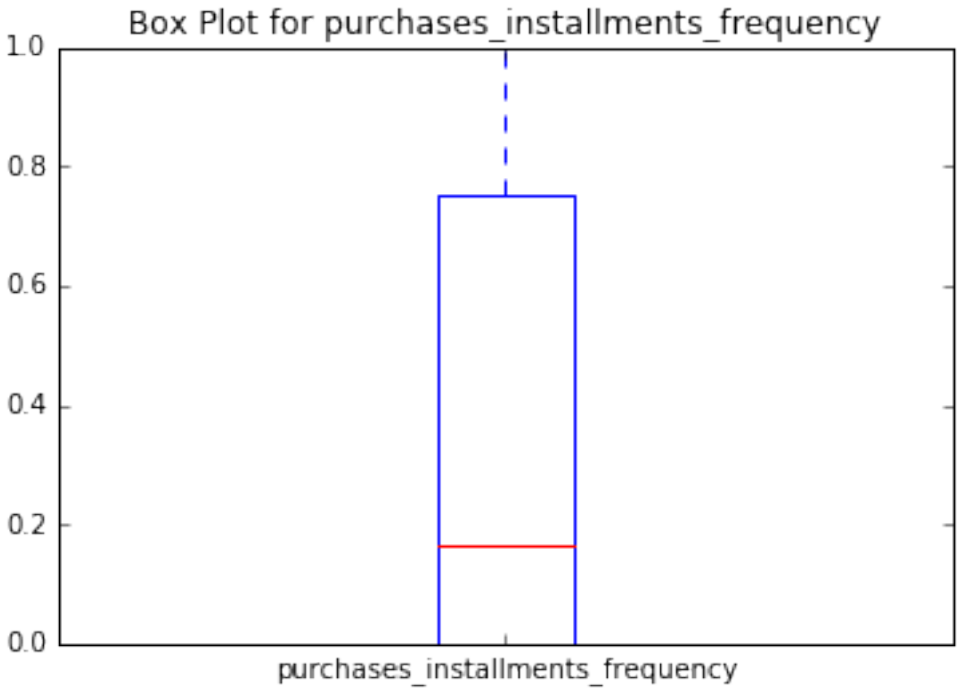

Box Plot for oneoff_purchases
45000
40000
35000
30000
25000
20000
15000
10000
5000
0
oneoff_purchases

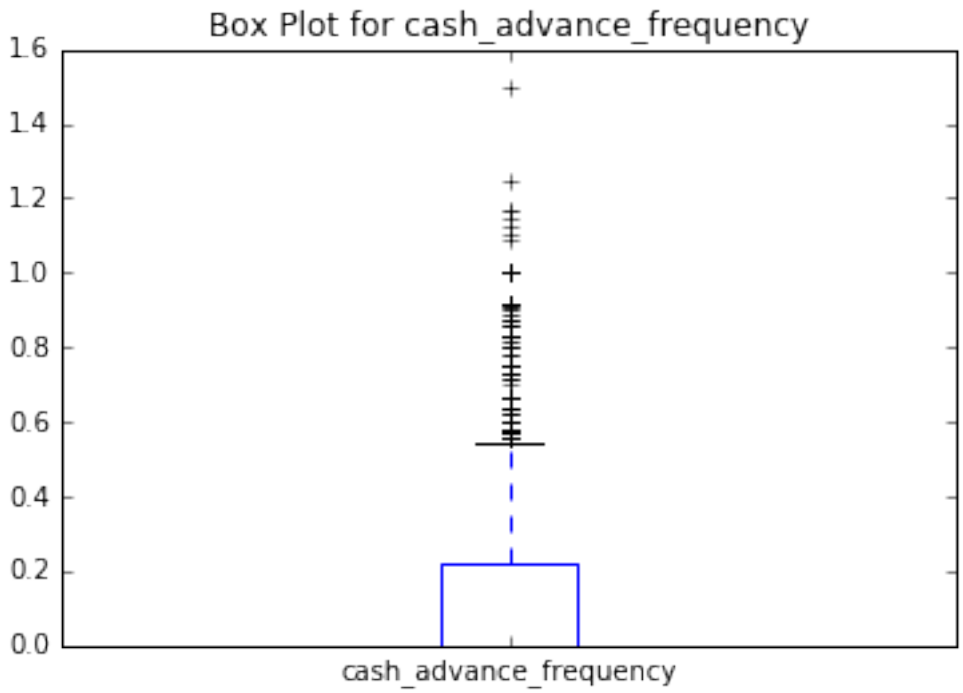

Box Plot for installments_purchases
25000
20000
15000
10000
5000
0
installments_purchases

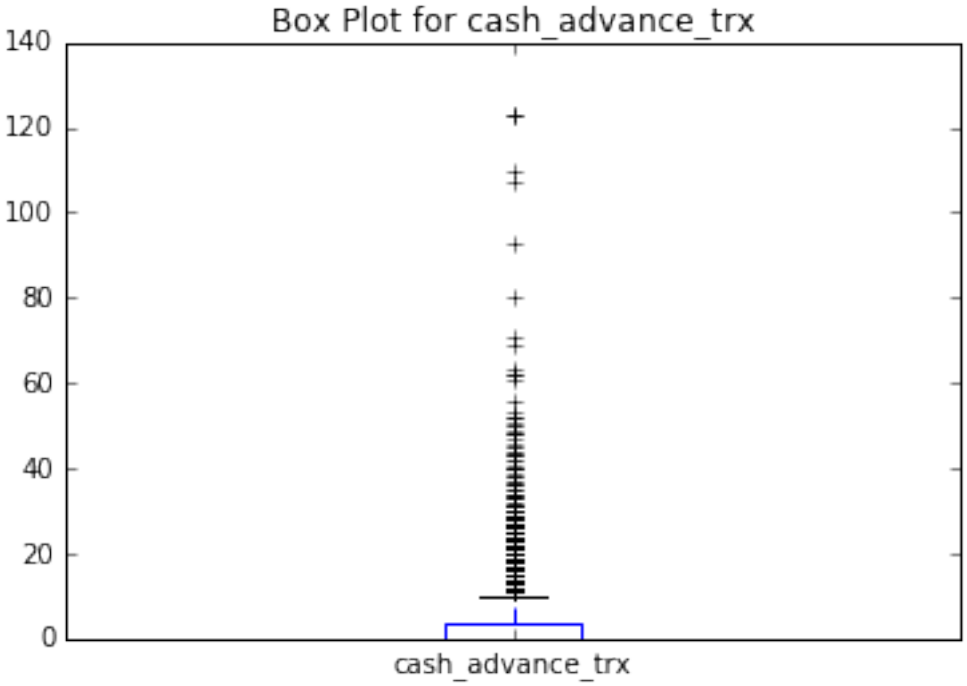

Box Plot for cash_advance
50000
40000
30000
20000
10000
0
cash_advance

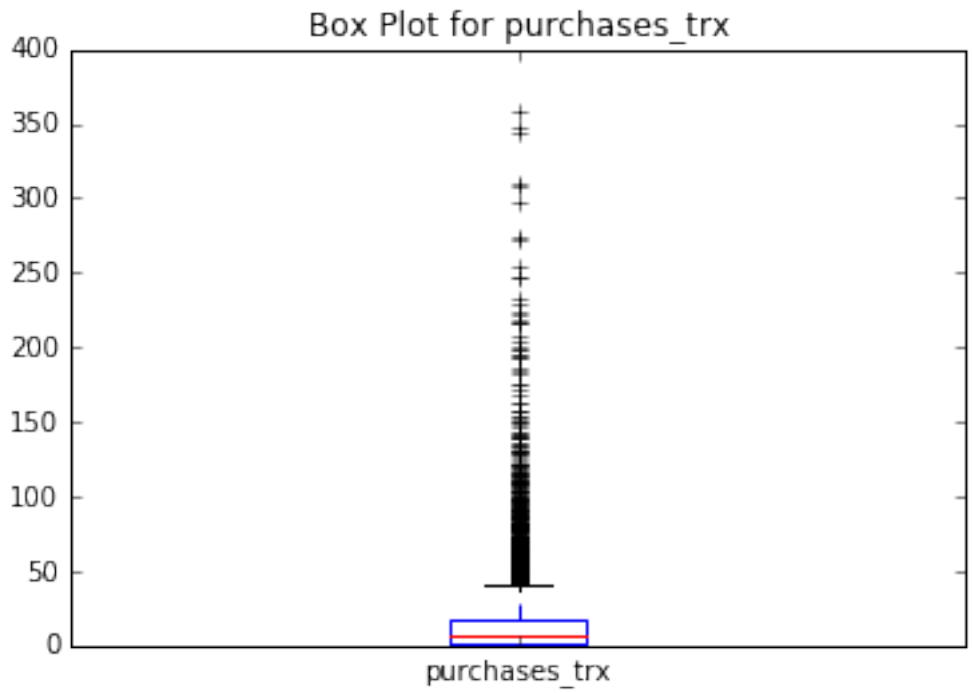

Box Plot for purchases_frequency
1.0
0.8
0.6
0.4
0.2
0.0
purchases_frequency

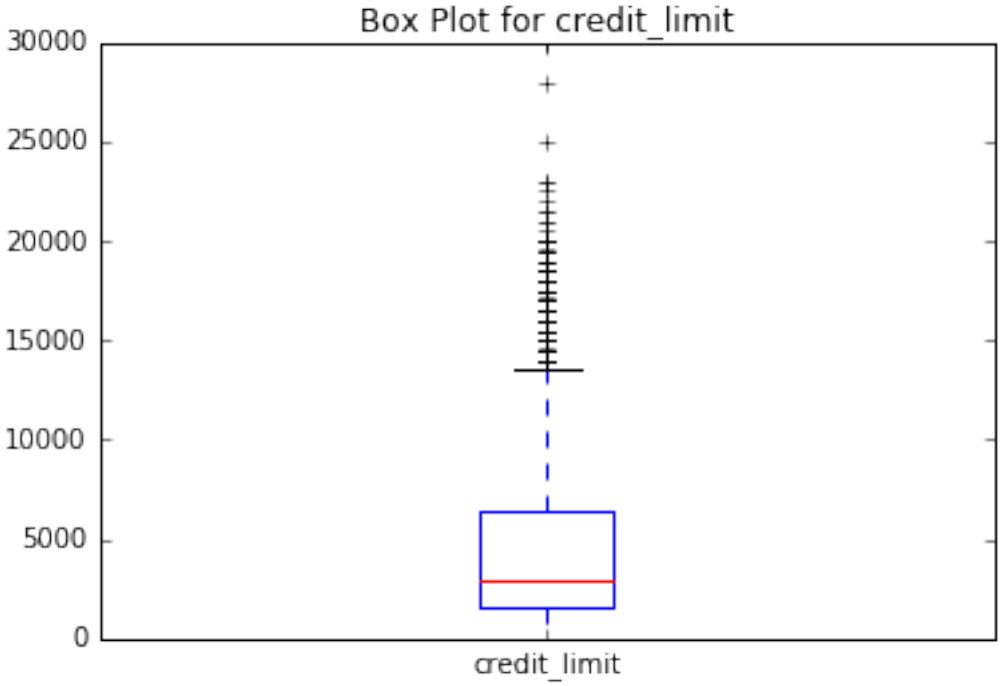

Box Plot for oneoff_purchases_frequency
1.0
0.8
0.6
0.4
0.2
0.0
oneoff_purchases_frequency

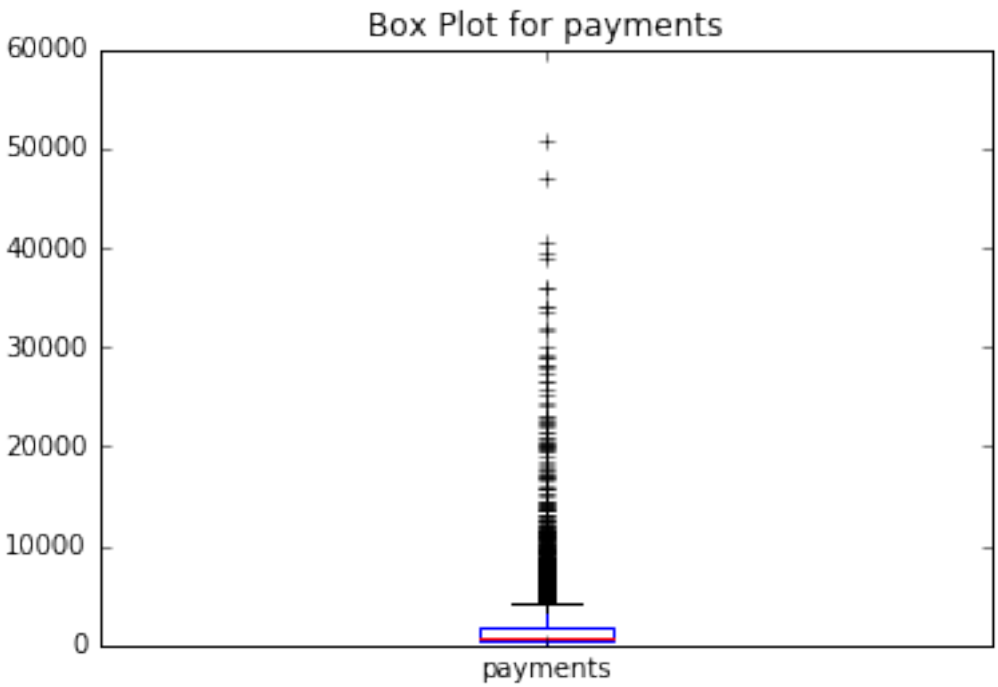

Box Plot for purchases_installments_frequency
1.0
0.8
0.6
0.4
0.2
0.0
purchases_installments_frequency

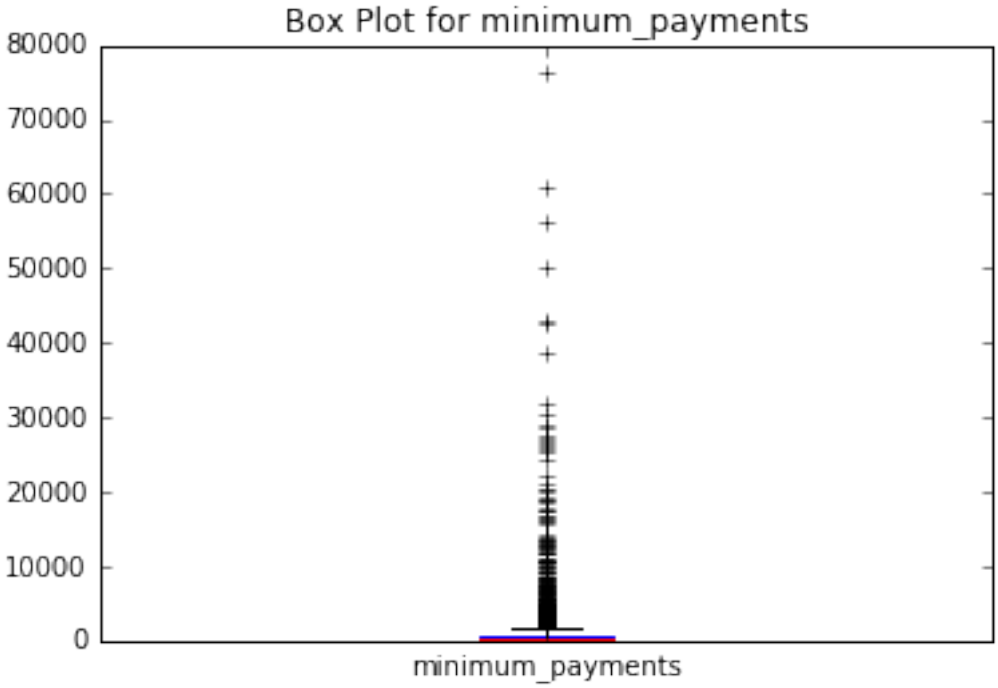

Box Plot for cash_advance_frequency
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
cash_advance_frequency

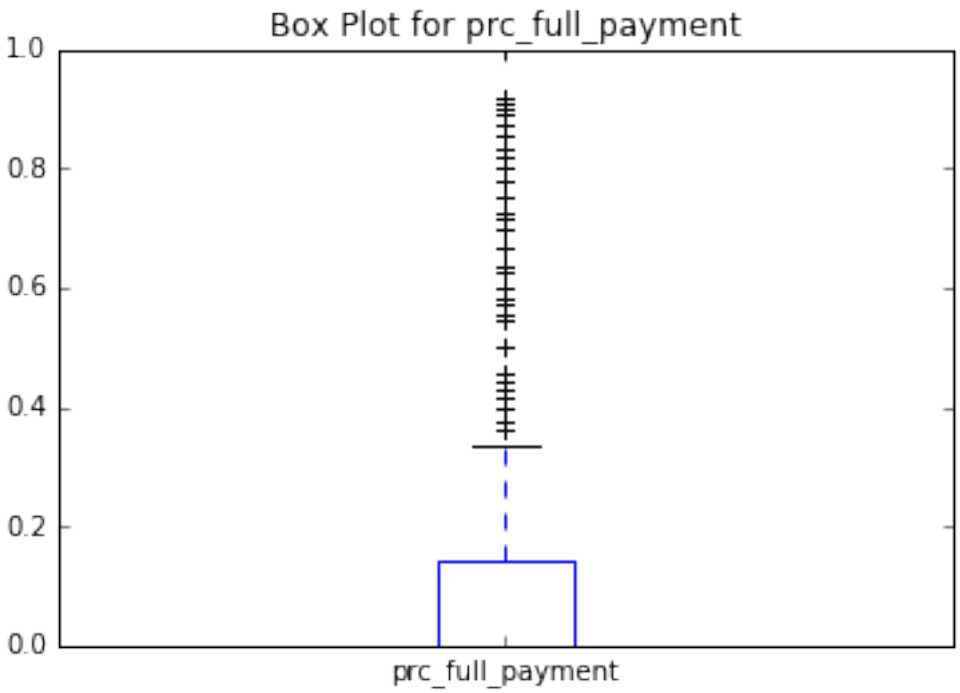

Box Plot for cash_advance_trx
140
120
100
80
60
40
20
0
cash_advance_trx

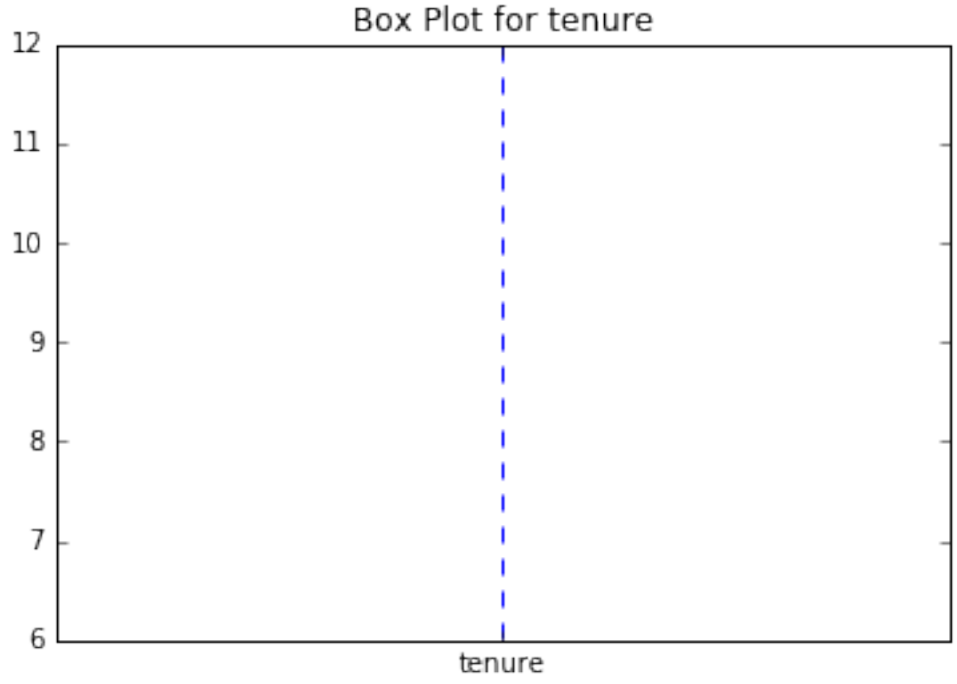

Box Plot for purchases_trx
400
350
300
250
200
150
100
50
0
purchases_trx


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


Box Plot for tenure
12
11
10
9
8
7
6
tenure

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

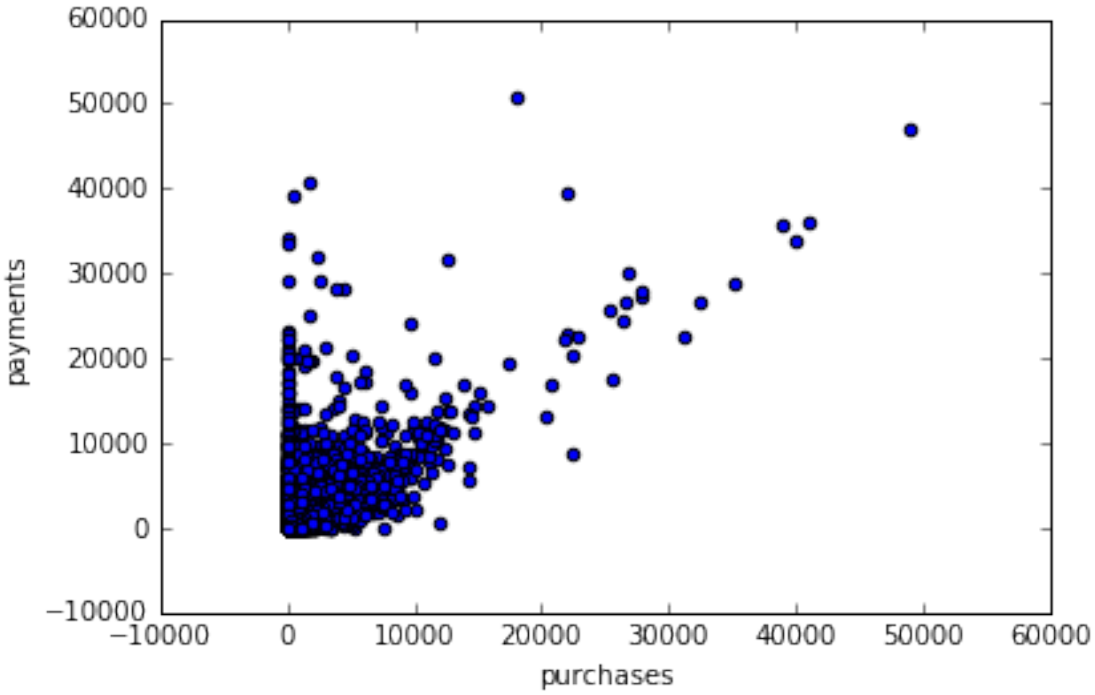
If that is the case, we could offer different payment plans based on different purchases.

```
In [58]: cluster_data = data[['purchases','payments']]
         cluster_data.head()
```

```
Out[58]:    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 [59]: cluster_data.plot(kind='scatter',x='purchases',y='payments')
```

```
Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7e41896b00>
```




```
In [60]: # 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() )
```

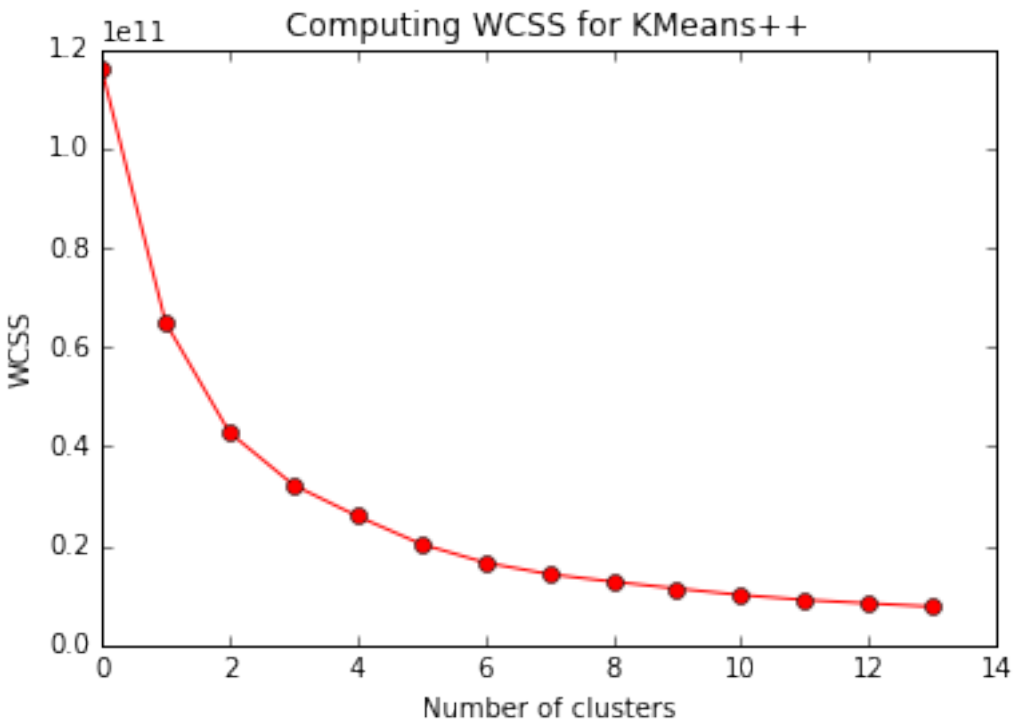
```
purchases    0
payments     0
dtype: int64
```

```
In [61]: #retrieve just the values for all columns except customer id
         data_values = cluster_data.iloc[ :, :].values
         data_values
```

```
Out[61]: array([[  95.4     ,  201.802084],
                [   0.      , 4103.032597],
                [ 773.17    ,  622.066742],
                ...,
                [ 144.4     ,   81.270775],
                [   0.      ,   52.549959],
                [1093.25    ,   63.165404]])
```

```
In [62]: #import KMeans algorithm
         from sklearn.cluster import KMeans
```

```
In [63]: # 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 5, so let's try 5 groups

```
In [64]: kmeans = KMeans(n_clusters=5, 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[64]:

	purchases	payments	cluster
0	95.40	201.802084	0
1	0.00	4103.032597	4
2	773.17	622.066742	0
3	1499.00	0.000000	0
4	16.00	678.334763	0
5	1333.28	1400.057770	0
6	7091.01	6354.314328	3
7	436.20	679.065082	0
8	861.49	688.278568	0
9	1281.60	1164.770591	0

10	920.12	1083.301007	0
11	1492.18	705.618627	0
12	3217.99	608.263689	0
13	2137.93	1655.891435	0
14	0.00	805.647974	0
15	1611.70	1993.439277	0
16	0.00	391.974562	0
17	519.00	254.590662	0
18	504.35	1720.837373	0
19	398.64	1053.980464	0
20	176.68	223.068600	0
21	6359.95	2077.959051	4
22	815.90	2359.629958	0
23	4248.35	9479.043842	3
24	0.00	1422.726707	0
25	399.60	215.306142	0
26	102.00	890.178845	0
27	233.28	207.773715	0
28	387.05	1601.448347	0
29	100.00	160.767773	0
...	...	...	...
8920	0.00	54.795084	0
8921	57.42	68.462579	0
8922	145.98	53.676054	0
8923	1898.88	669.039640	0
8924	74.00	214.921009	0
8925	418.59	422.538988	0
8926	580.00	641.303466	0
8927	315.20	231.274641	0
8928	500.00	456.745027	0
8929	0.00	0.000000	0
8930	84.00	124.373736	0
8931	235.80	189.090274	0
8932	180.00	138.203240	0
8933	619.60	106.138603	0
8934	110.50	161.476789	0
8935	465.90	0.000000	0
8936	712.50	605.716356	0
8937	0.00	117.738787	0
8938	0.00	1397.770131	0
8939	734.40	72.530037	0
8940	591.24	475.523262	0
8941	214.55	966.202912	0
8942	113.28	94.488828	0
8943	20.90	58.644883	0
8944	1012.73	0.000000	0
8945	291.12	325.594462	0
8946	300.00	275.861322	0

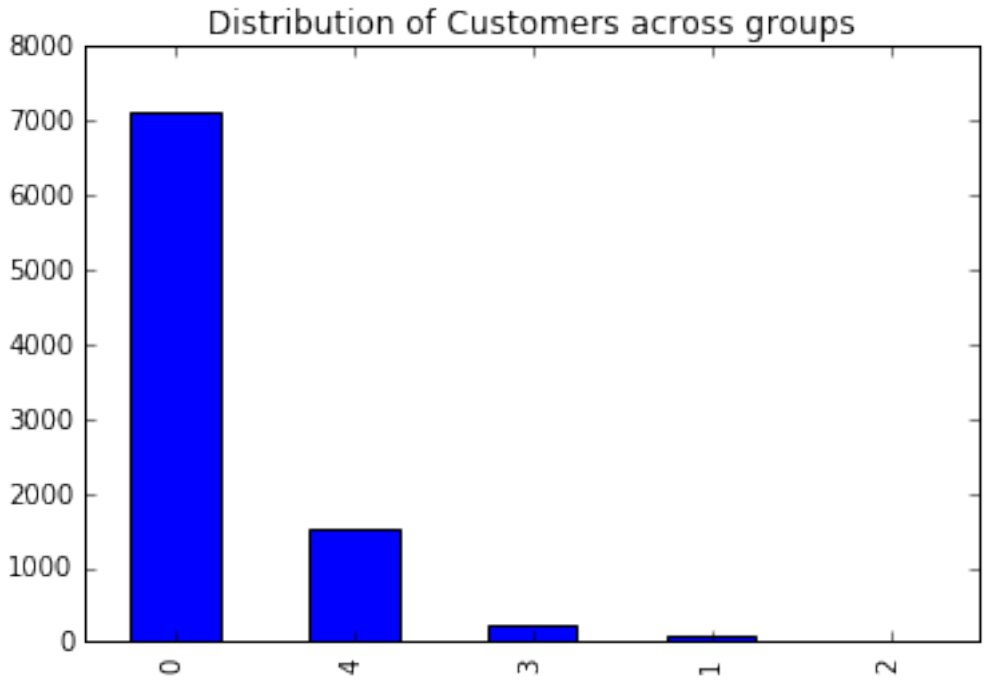
```
8947     144.40    81.270775        0
8948       0.00    52.549959        0
8949    1093.25    63.165404        0

[8950 rows x 3 columns]
```

```
In [65]: cluster_data['cluster'].value_counts()
```

```
Out[65]: 0    7101
         4    1506
         3     225
         1      95
         2      23
         Name: cluster, dtype: int64
```

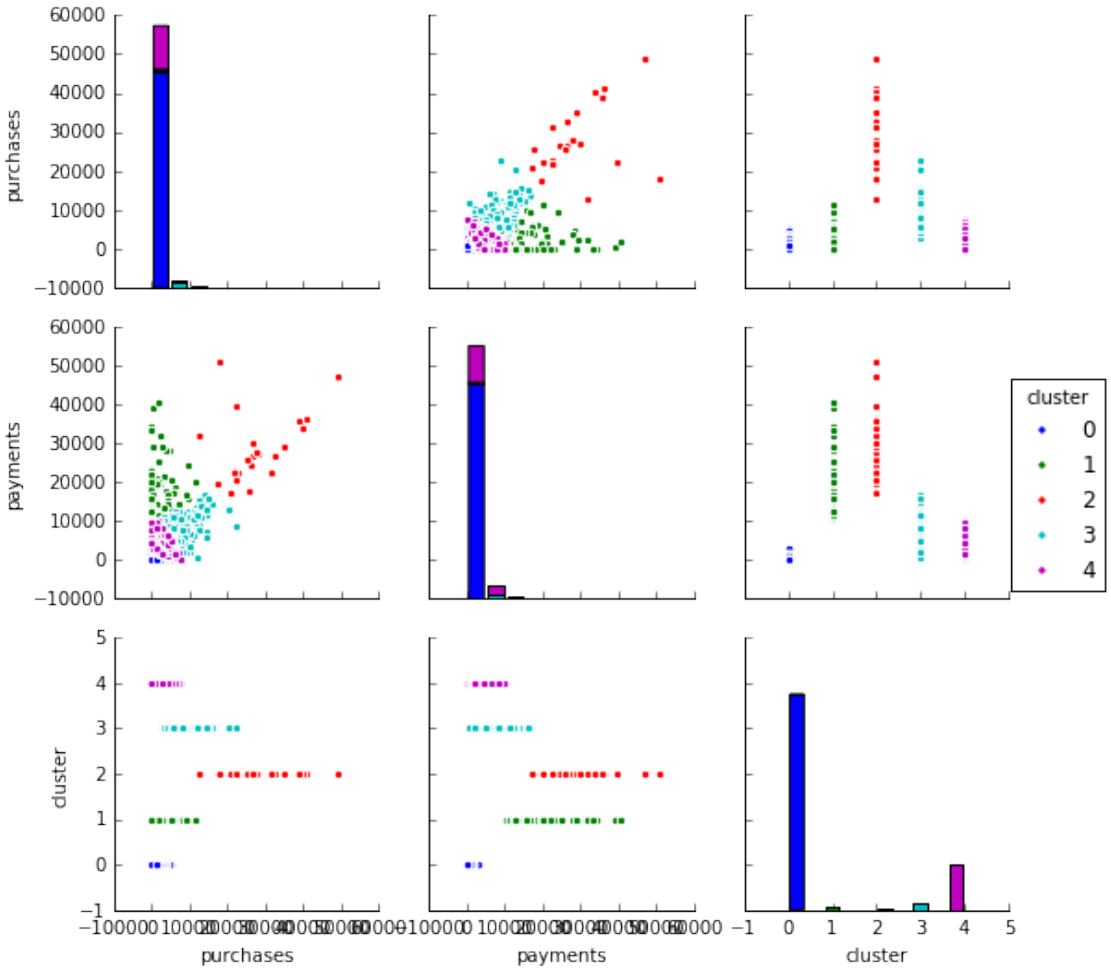
```
In [66]: cluster_data['cluster'].value_counts().plot(kind='bar',title='Distribution of Customers
```

```
Out[66]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7e4185f9b0>
```




```
In [67]: sns.pairplot( cluster_data, hue="cluster")
```

```
Out[67]: <seaborn.axisgrid.PairGrid at 0x7f7e4188ffd0>
```



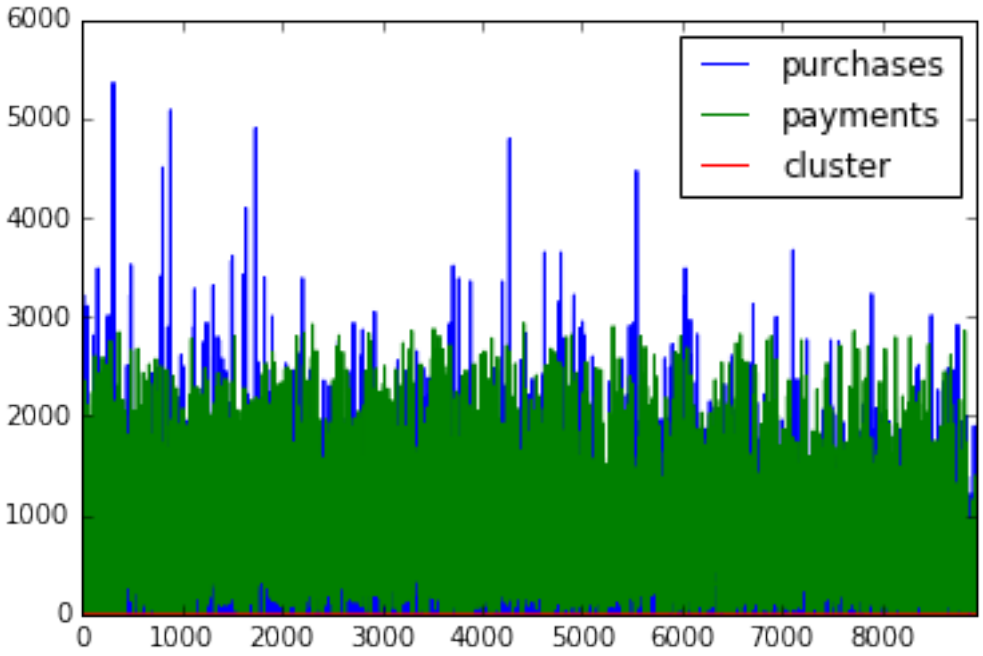
Looks nice, but what are we really seeing? Let's attempt to describe the groups

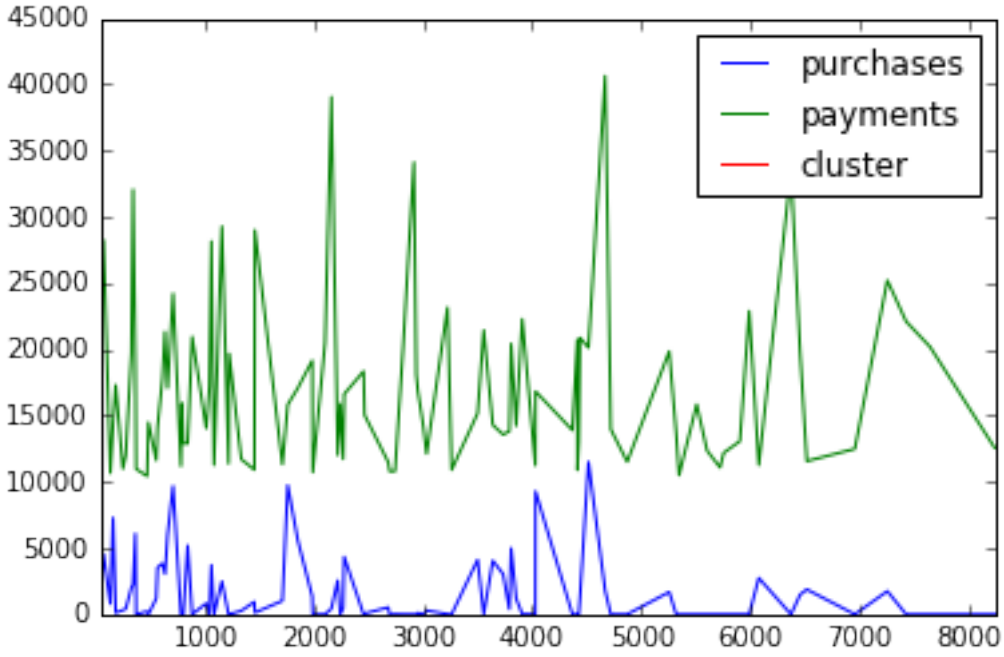
```
In [68]: grouped_cluster_data = cluster_data.groupby('cluster')
         grouped_cluster_data

Out[68]: <pandas.core.groupby.DataFrameGroupBy object at 0x7f7e4180b898>

In [69]: grouped_cluster_data.describe()

Out[69]:                    purchases      payments  cluster
         cluster
         0       count   7101.000000   7101.000000     7101
                 mean     490.956174    791.841069        0
                 std      614.496323    613.360202        0
                 min        0.000000      0.000000        0
                 25%        9.900000    311.599140        0
                 50%      268.920000    617.883193        0
                 75%      715.810000   1164.081703        0
```

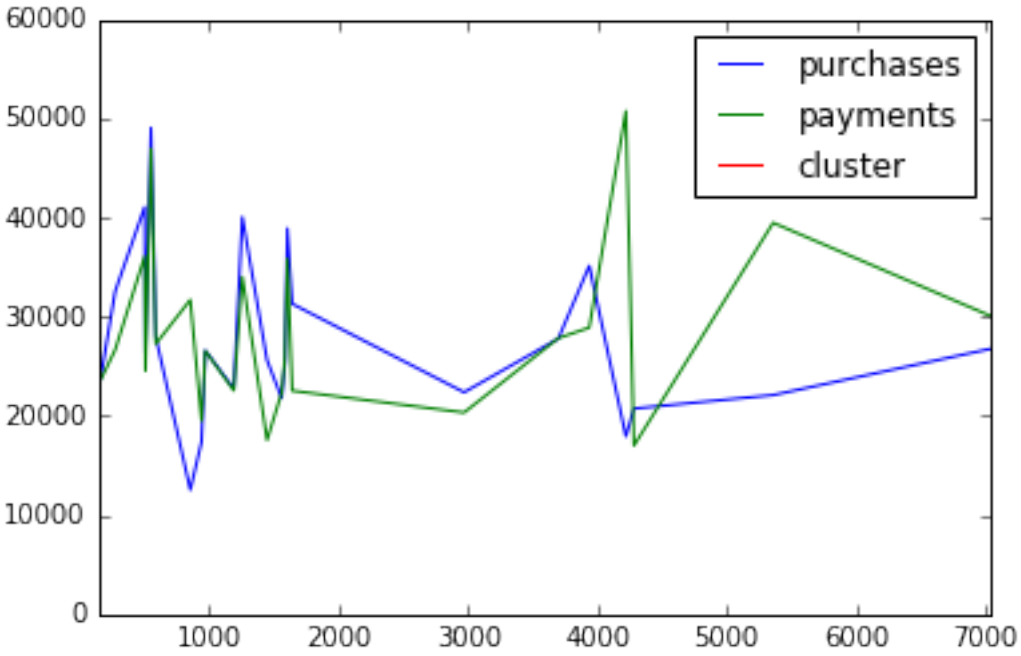
```
                max     5359.020000   2933.325551        0
1               count     95.000000     95.000000       95
                mean    1511.432632  17020.850174        1
                std     2500.194731   6511.217645        0
                min        0.000000  10428.376110        1
                25%        0.000000  11863.586565        1
                50%      130.240000  15043.665080        1
                75%     1943.560000  20096.540445        1
                max    11500.940000  40627.595240        1
2               count     23.000000     23.000000       23
                mean   27574.397391  28574.474955        2
                std     8650.801231   8731.018481        0
                min    12551.950000  17005.409690        2
                25%    22055.850000  22550.435810        2
                50%    26402.390000  26652.344320        2
                75%    31919.565000  32846.573435        2
                max    49039.570000  50721.483360        2
3               count    225.000000    225.000000      225
                mean    7841.268444   7504.859576        3
                std     2990.571070   2963.414587        0
                min     2823.800000    508.797444        3
                25%     5787.660000   5589.952268        3
                50%     7244.980000   7109.795209        3
                75%     9321.130000   9290.702248        3
                max    22500.000000  16826.424430        3
4               count   1506.000000   1506.000000     1506
                mean    1959.044376   3934.918291        4
                std     1612.348685   1793.904174        0
                min        0.000000      0.000000        4
                25%      348.500000   2662.342657        4
                50%     1940.400000   3502.654096        4
                75%     3095.712500   4644.258312        4
                max     7597.090000  10339.938450        4
```

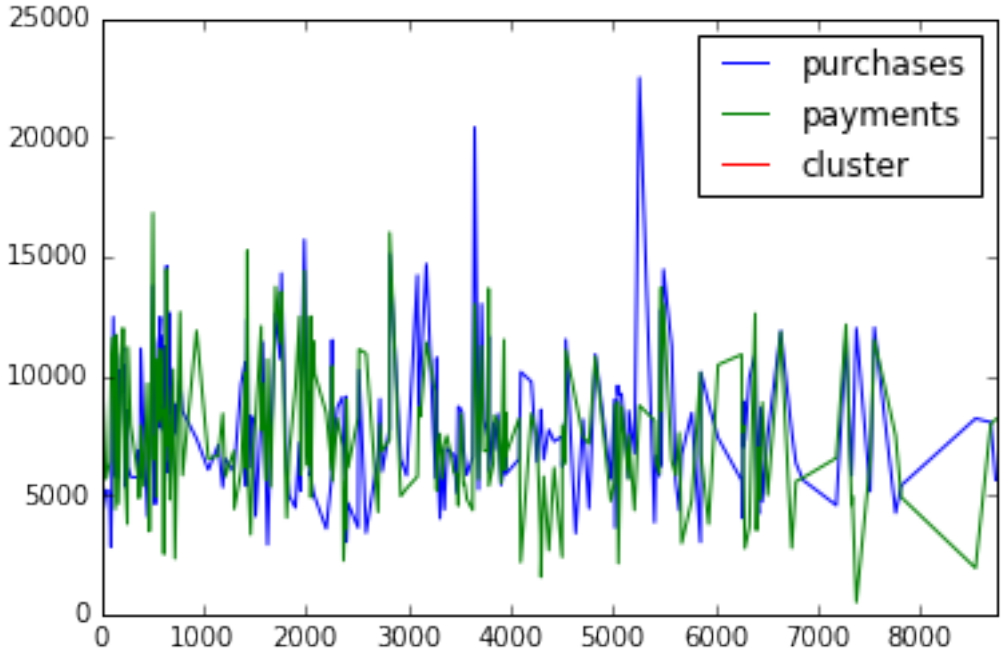
In [70]:
```
grouped_cluster_data.plot(subplots=True,)
```

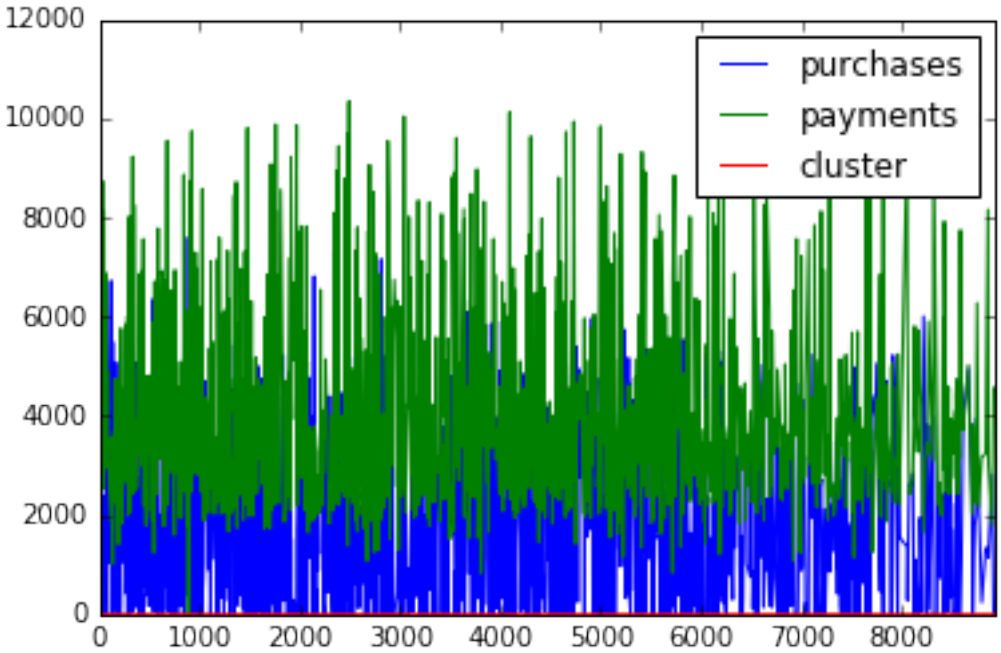
Out[70]:
```
cluster
0    Axes(0.125,0.125;0.775x0.775)
1    Axes(0.125,0.125;0.775x0.775)
2    Axes(0.125,0.125;0.775x0.775)
3    Axes(0.125,0.125;0.775x0.775)
4    Axes(0.125,0.125;0.775x0.775)
dtype: object
```


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


purchases
payments
cluster
45000
40000
35000
30000
25000
20000
15000
10000
5000
0
1000
2000
3000
4000
5000
6000
7000
8000


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


25000
20000
15000
10000
5000
0
0
1000
2000
3000
4000
5000
6000
7000
8000
purchases
payments
cluster



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

```
In [77]: kmeans.predict(pd.DataFrame({'purchases':[300],'payments':[40000]}))

Out[77]: array([2], dtype=int32)

In [72]: help(kmeans.predict)

Help on method predict in module sklearn.cluster.k_means_:

predict(X) method of sklearn.cluster.k_means_.KMeans instance
    Predict the closest cluster each sample in X belongs to.

    In the vector quantization literature, `cluster_centers_` is called
    the code book and each value returned by `predict` is the index of
    the closest code in the code book.

    Parameters
    ----------
    X : {array-like, sparse matrix}, shape = [n_samples, n_features]
        New data to predict.
```

```
    Returns
    -------
    labels : array, shape [n_samples,]
        Index of the cluster each sample belongs to.
```

```
In [73]: kmeans.predict([[3,2]])
```

```
Out[73]: array([0], dtype=int32)
```

```
In [74]: kmeans.algorithm
```

```
Out[74]: 'auto'
```

```
In [75]: kmeans.cluster_centers_
```

```
Out[75]: array([[  491.02532254,   791.53945193],
                [ 1511.43263158, 17020.85017389],
                [27574.3973913 , 28574.47495522],
                [ 7841.26844444,  7504.8595756 ],
                [ 1957.74441274,  3934.25366418]])
```

```
In [76]: kmeans
```

```
Out[76]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
             n_clusters=5, n_init=10, n_jobs=1, precompute_distances='auto',
             random_state=None, tol=0.0001, verbose=0)
```