In this notebook I will try to find a possible customer segmenetation enabling to classify customers according the their different purchases. I hope this information will be useful for the next prediction task. Since there are thousands of products in the dataset I will rely on aisles, which represent categories of products. Even with aisles features will be too much so I will use Principal Component Analysis to find new dimensions along which clustering will be easier. I will then try to find possible explanations for the identified clusters.

First Exploration

Data Dictionary: https://gist.github.com/jeremystan/c3b39d947d9b88b3ccff3147dbcf6c6b

Market Basket Analysis data (Kaggle): https://www.kaggle.com/c/instacart-market-basket-analysis/data

Instacart Data (public release - article): https://tech.instacart.com/3-million-instacart-orders-open-sourced-d40d29ead6f2

Citation to add to notebook: “The Instacart Online Grocery Shopping Dataset 2017”, Accessed from https://www.instacart.com/datasets/grocery-shopping-2017

PCA-using-python-scikit-learn : https://towardsdatascience.com/pca-using-python-scikit-learn-e653f8989e60

Customer segments with PCA: https://www.kaggle.com/asindico/customer-segments-with-pca

Step By Step PCA Math: https://builtin.com/data-science/step-step-explanation-principal-component-analysis

In [1]:

```
import numpy as np
import pandas as pd
```

In [2]:

```
import os
os.chdir("D:\WorkRepo\instacart-market-basket-analysis\instacart-market-basket-analysis
```

In [10]:

```
orders = pd.read_csv('orders.csv')
prior = pd.read_csv('order_products__prior.csv')
```

In [11]:

```
orders.groupby(orders['eval_set']).count()
```

Out[11]:

	order_id	user_id	order_number	order_dow	order_hour_of_day	days_since_prior_order
eval_set						
prior	3214874	3214874	3214874	3214874	3214874	3008665
test	75000	75000	75000	75000	75000	75000
train	131209	131209	131209	131209	131209	131209

In [18]:

```
prior.count()
# prior dataset contains more records than order dataset - we can take care of this whe
```

Out[18]:

```
order_id                 32434489
```

```
product_id           32434489
add_to_cart_order    32434489
reordered            32434489
dtype: int64
```

In [16]:
```
# Where is my file? Find save location
# https://stackoverflow.com/questions/18901185/ipython-notebook-save-location
#!ipython locate
# Default: C:\Users\Vineet PC\.ipython
```

```
C:\Users\Vineet PC\.ipython
```

In [19]:
```
##Due to the number of rows I have to reduce the set of prior data to publish the kerne
##comment this if you execute it on your local machine
prior = prior[0:300000]
```

Merge two datasets

In [20]:
```
order_prior = pd.merge(prior,orders,on=['order_id','order_id'])
order_prior = order_prior.sort_values(by=['user_id','order_id'])
order_prior.head()
```

Out[20]:

	order_id	product_id	add_to_cart_order	reordered	user_id	eval_set	order_number	order_dow
221645	23391	13198	1	1	7	prior	17	0
221646	23391	42803	2	1	7	prior	17	0
221647	23391	8277	3	1	7	prior	17	0
221648	23391	37602	4	1	7	prior	17	0
221649	23391	40852	5	1	7	prior	17	0

In [21]:
```
order_prior.count()
```

Out[21]:
```
order_id                  300000
product_id                300000
add_to_cart_order         300000
reordered                 300000
user_id                   300000
eval_set                  300000
order_number              300000
order_dow                 300000
order_hour_of_day         300000
days_since_prior_order    280806
dtype: int64
```

In [22]:
```
print(order_prior.shape)
```

```
(300000, 10)
```

Now loading Products and Aisles datasets and merging them with order_prior

In [23]:
```
products = pd.read_csv('products.csv')
aisles = pd.read_csv('aisles.csv')
```

In [26]:
```
products.count()
```

Out[26]:
```
product_id      49688
product_name    49688
```

```
aisle_id         49688
department_id    49688
dtype: int64
```

In [24]:
```
data = pd.merge(prior,products, on = ['product_id','product_id'])
data = pd.merge(data,orders,on=['order_id','order_id'])
data = pd.merge(data,aisles,on=['aisle_id','aisle_id'])
data.head(10)
```

Out[24]:

	order_id	product_id	add_to_cart_order	reordered	product_name	aisle_id	department_id	user_id
0	2	33120	1	1	Organic Egg Whites	86	16	202279
1	26	33120	5	0	Organic Egg Whites	86	16	153404
2	120	33120	13	0	Organic Egg Whites	86	16	23750
3	327	33120	5	1	Organic Egg Whites	86	16	58707
4	390	33120	28	1	Organic Egg Whites	86	16	166654
5	537	33120	2	1	Organic Egg Whites	86	16	180135
6	582	33120	7	1	Organic Egg Whites	86	16	193223
7	608	33120	5	1	Organic Egg Whites	86	16	91030
8	623	33120	1	1	Organic Egg Whites	86	16	37804
9	689	33120	4	1	Organic Egg Whites	86	16	108932

In [25]:
```
data.shape
```

Out[25]: (300000, 14)

In [ ]:
```
# Sneakpeak into product names in products dataset
data['product_name'].value_counts()[0:10]
```

In [30]:
```
# Count of unique products in the dataset
len(data['product_name'].unique())
```

Out[30]: 24836

In [32]:
```
# Sneakpeak into aisle names in aisles dataset
data['aisle'].value_counts()[0:10]
```

Out[32]:
```
fresh fruits                    33755
fresh vegetables                31004
packaged vegetables fruits      16319
yogurt                          13477
```

```
packaged cheese                 9133
milk                            8254
water seltzer sparkling water   7634
chips pretzels                  6581
soy lactosefree                 5965
bread                           5457
Name: aisle, dtype: int64
```

Principal Component Analysis

Reading 1 and 2 we got to know that we can speed up the fitting of a machine learning algorithm by changing the optimization algorithm. A more common way of speeding up a machine learning algorithm is by using Principal Component Analysis (PCA). If your learning algorithm is too slow because the input dimension is too high, then using PCA to speed it up can be a reasonable choice. This is probably the most common application of PCA. Another common application of PCA is for data visualization.

SKLEARN PCA Library: https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.PCA.html

References:

In order to determine possible clusters among the customers, single user_id will need to be substituted with the specific cluster to which they are assumed to belong. Fro this I will create a crosstab of user_id with **aisle** (representing product category).

This should perhaps eventually increase the next prediction model performance.

-> Creating a dataframe with all the purchases made by each user

In [43]:
```
cust_prod = pd.crosstab(data['user_id'], data['aisle'])
cust_prod.head(10)
#cust_prod.shape
```

Out[43]:

aisle	air fresheners candles	asian foods	baby accessories	baby bath body care	baby food formula	bakery desserts	baking ingredients	baking supplies decor	beauty	beers coolers
user_id										
7	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	1	0	0	0
23	0	0	0	0	0	0	0	0	1	0
27	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	1
42	0	0	0	0	0	0	0	0	0	0
66	0	0	0	0	0	0	1	0	0	0
67	0	0	0	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	1	0	0	0

10 rows × 134 columns

Applying PCA from SKLEARN

In [38]:
```
# !pip install sklearn
```

```
Collecting sklearn
  Downloading sklearn-0.0.tar.gz (1.1 kB)
Collecting scikit-learn
  Downloading scikit_learn-0.23.2-cp38-cp38-win_amd64.whl (6.8 MB)
Requirement already satisfied: numpy>=1.13.3 in d:\anaconda3\lib\site-packages (from sci
kit-learn->sklearn) (1.19.4+vanilla)
Collecting joblib>=0.11
  Downloading joblib-0.17.0-py3-none-any.whl (301 kB)
Collecting scipy>=0.19.1
  Downloading scipy-1.5.4-cp38-cp38-win_amd64.whl (31.4 MB)
Collecting threadpoolctl>=2.0.0
  Using cached threadpoolctl-2.1.0-py3-none-any.whl (12 kB)
Building wheels for collected packages: sklearn
  Building wheel for sklearn (setup.py): started
  Building wheel for sklearn (setup.py): finished with status 'done'
  Created wheel for sklearn: filename=sklearn-0.0-py2.py3-none-any.whl size=1321 sha256=
b70bab0ede83657255064a5b829fedfa154db743b2dd7b9330d4c0e4a68d62f0
  Stored in directory: c:\users\vineet pc\appdata\local\pip\cache\wheels\22\0b\40\fd3f79
5caaa1fb4c6cb738bc1f56100be1e57da95849bfc897
Successfully built sklearn
Installing collected packages: joblib, scipy, threadpoolctl, scikit-learn, sklearn
Successfully installed joblib-0.17.0 scikit-learn-0.23.2 scipy-1.5.4 sklearn-0.0 threadp
oolctl-2.1.0
```

In [55]:
```
from sklearn.decomposition import PCA
pca = PCA(n_components=6)
pca.fit(cust_prod)
pca_samples = pca.transform(cust_prod)
```

In [56]:
```
#type(pca_samples)
pca_samples = pd.DataFrame(pca_samples, columns = ['PC1', 'PC2', 'PC3', 'PC4','PC5', 'P
```

In [57]:
```
pca_samples.head(5)
```

Out[57]:

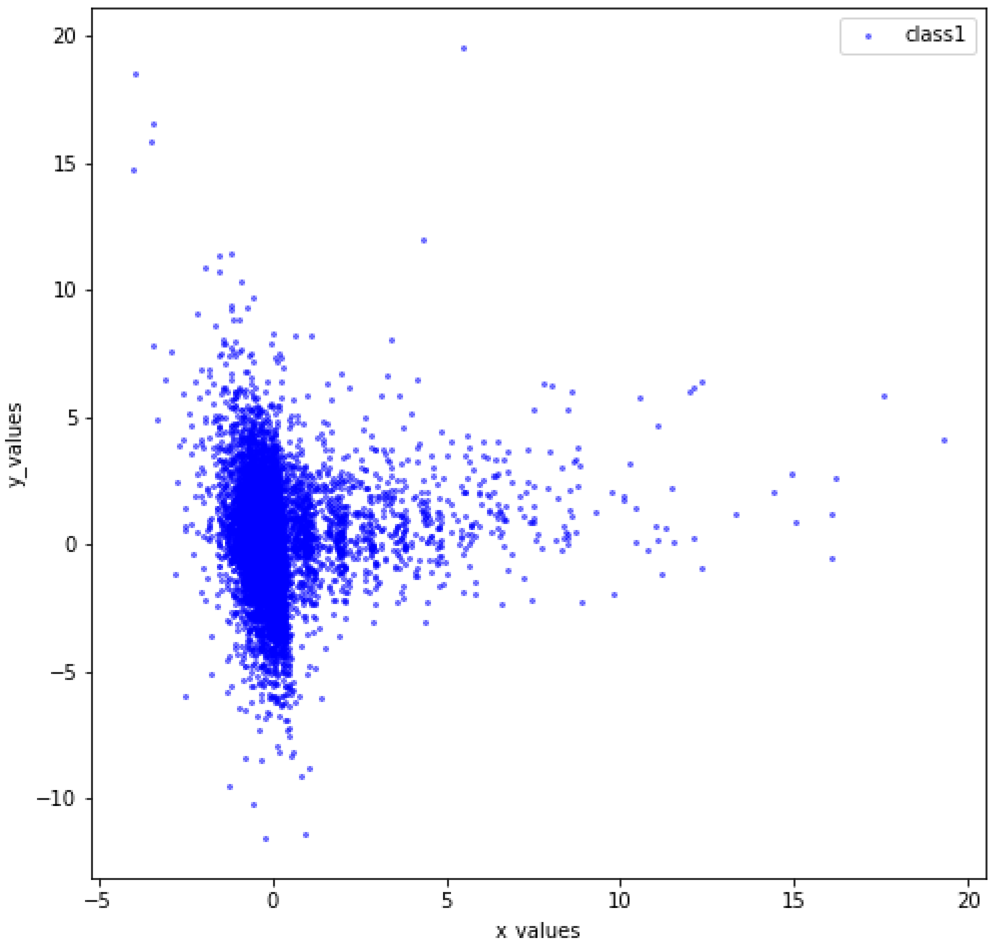
	PC1	PC2	PC3	PC4	PC5	PC6
0	-0.286251	1.005868	-1.030292	-0.898964	-0.587675	-0.998982
1	-1.972748	-0.487659	-0.120541	0.213091	0.045931	-0.182132
2	-1.168974	1.284089	3.228124	0.594045	-0.648822	-1.091778
3	-1.433967	1.250081	3.261985	1.237737	-0.353525	-0.346412
4	-2.070709	-0.422148	-0.101553	0.278129	0.005933	-0.097450

Visualizing the principal components (PC2 and PC5)

In [60]:
```
from matplotlib import pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
from mpl_toolkits.mplot3d import proj3d
tocluster = pd.DataFrame(pca_samples[['PC5','PC2']])
print (tocluster.shape)
```

```
print (tocluster.head())

fig = plt.figure(figsize=(8,8))
plt.plot(tocluster['PC5'], tocluster['PC2'], 'o', markersize=2, color='blue', alpha=0.5

plt.xlabel('x_values')
plt.ylabel('y_values')
plt.legend()
plt.show()
```

```
(25831, 2)
        PC5       PC2
0 -0.587675  1.005868
1  0.045931 -0.487659
2 -0.648822  1.284089
3 -0.353525  1.250081
4  0.005933 -0.422148
```



In [61]:
```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

clusterer = KMeans(n_clusters=4,random_state=42).fit(tocluster)
centers = clusterer.cluster_centers_
c_preds = clusterer.predict(tocluster)
print(centers)
```

```
[[-0.04620596 -0.15279047]
 [-0.00851022 -2.39783038]
 [-0.24921441  2.06678283]
 [ 5.57233012  1.45511416]]
```

In [62]:
```
print (c_preds[0:100])
```

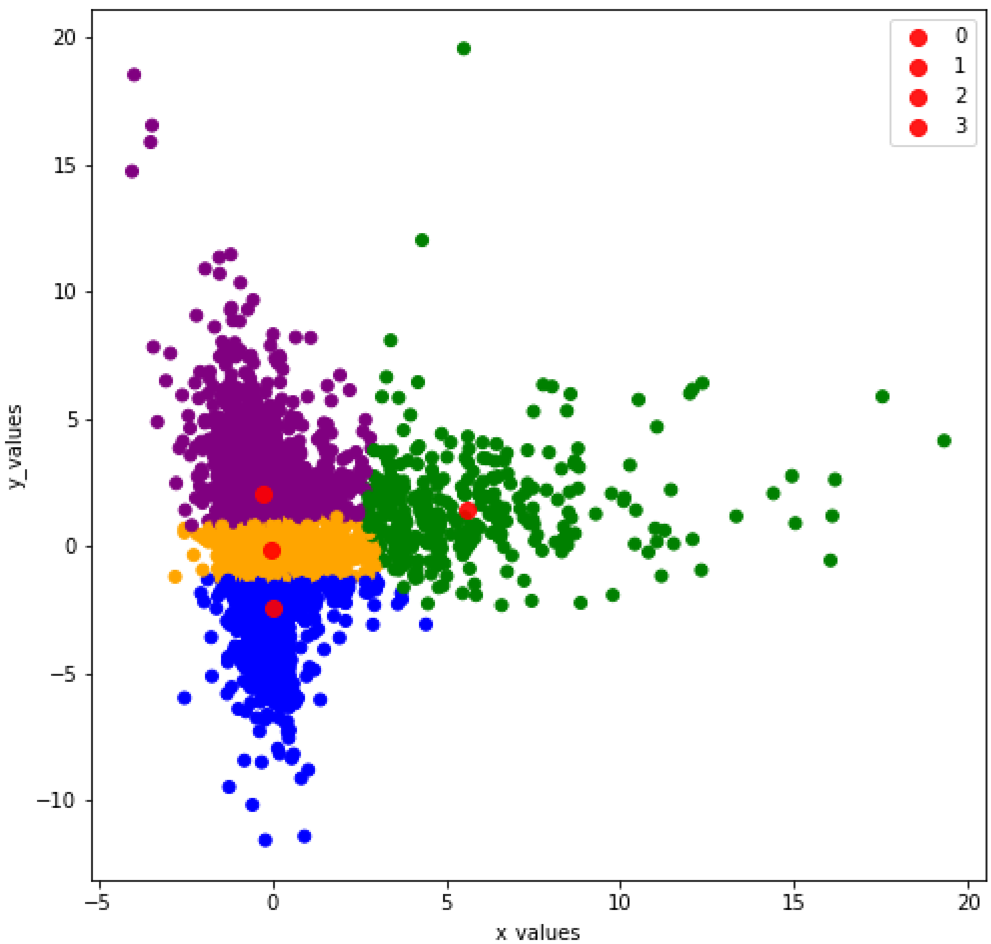
```
[2 0 2 2 0 0 0 0 0 0 1 0 2 0 0 3 0 0 2 0 0 0 0 0 0 2 1 0 0 2 0 0 0 0 0 0 0
 0 0 0 2 0 0 0 0 0 0 0 2 0 0 0 2 0 0 0 2 0 0 0 1 0 0 0 0 0 0 0 1 1 0 0 0 0
 2 2 1 0 0 0 0 0 2 2 0 0 1 2 0 0 0 0 0 2 0 0 2 0 0 0]
```

Visualizing the clusters

In [64]:

```python
import matplotlib
fig = plt.figure(figsize=(8,8))
colors = ['orange','blue','purple','green']
colored = [colors[k] for k in c_preds]
print (colored[0:10])
plt.scatter(tocluster['PC5'],tocluster['PC2'],  color = colored)
for ci,c in enumerate(centers):
    plt.plot(c[0], c[1], 'o', markersize=8, color='red', alpha=0.9, label=''+str(ci))

plt.xlabel('x_values')
plt.ylabel('y_values')
plt.legend()
plt.show()
```

```
['purple', 'orange', 'purple', 'purple', 'orange', 'orange', 'orange', 'orange', 'orang
e', 'orange']
```



We have found a possible clustering for our customers. Let's check if we also manage to find some interesting pattern beneath it.

In [72]:

```python
clust_prod = cust_prod.copy()
clust_prod['cluster'] = c_preds

clust_prod.head(10)
```

Out[72]:

aisle	air fresheners candles	asian foods	baby accessories	baby bath body care	baby food formula	bakery desserts	baking ingredients	baking supplies decor	beauty	beers coolers
user_id										
7	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	1	0	0	0
23	0	0	0	0	0	0	0	0	1	0
27	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	1
42	0	0	0	0	0	0	0	0	0	0
66	0	0	0	0	0	0	1	0	0	0
67	0	0	0	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	1	0	0	0

10 rows × 135 columns

See the shape of our product-clustrers dataframe for Cluster # 0

In [97]:

```
clust_prod[clust_prod['cluster']==0]
# 16294 rows × 135 columns
```

Out[97]:

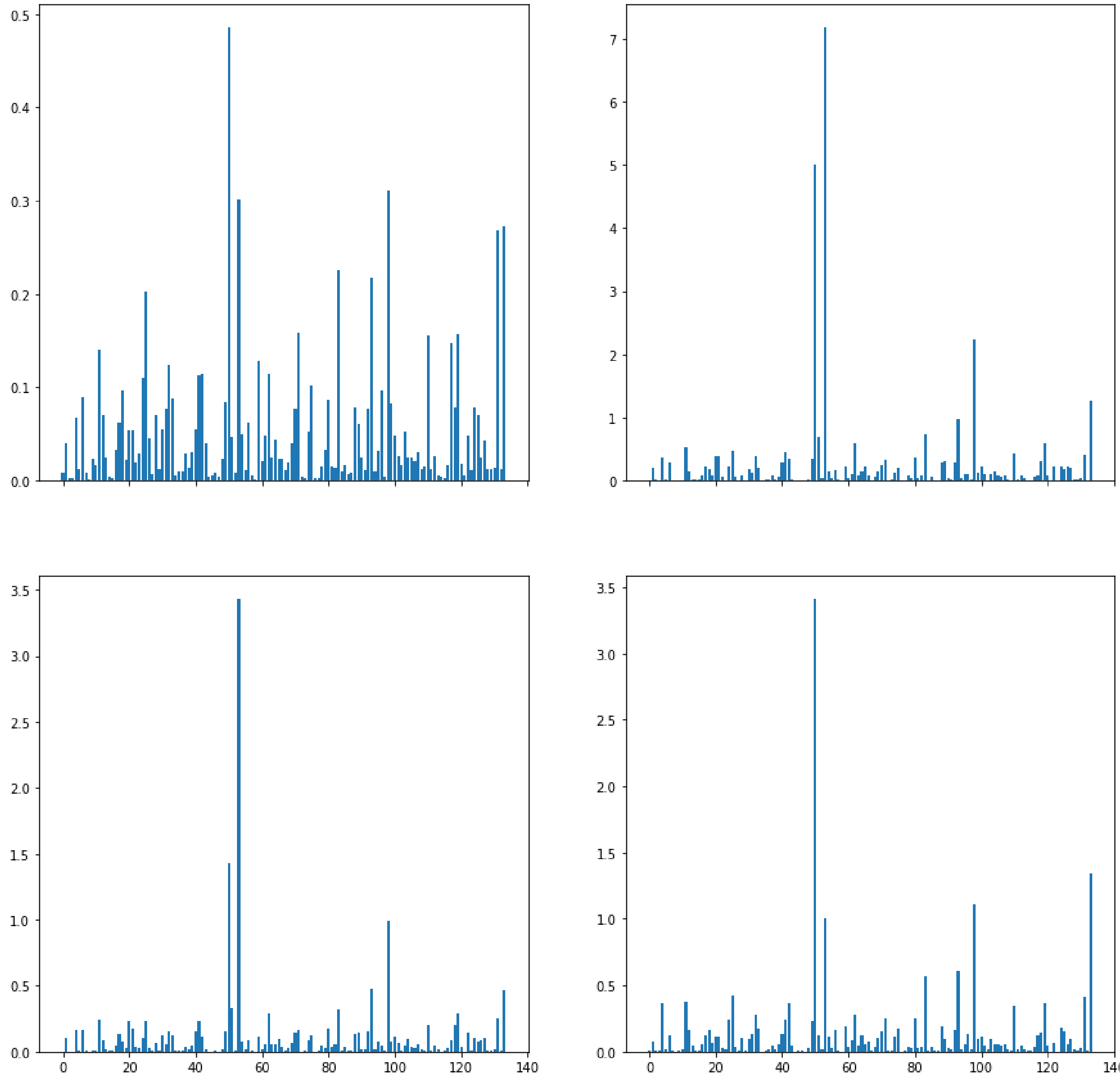
aisle	air fresheners candles	asian foods	baby accessories	baby bath body care	baby food formula	bakery desserts	baking ingredients	baking supplies decor	beauty	beers coolers
user_id										
7	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	1	0	0	0
23	0	0	0	0	0	0	0	0	1	0
27	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	1
...	...	...	...	...	...	...	...	...	...	...
206162	0	0	0	0	0	0	0	0	0	0
206165	0	0	0	0	0	0	0	0	0	0
206201	0	0	0	0	0	0	2	0	0	0
206206	0	0	0	0	0	0	0	0	0	0
206207	0	0	0	0	0	0	0	0	0	0

16294 rows × 135 columns

Creating subplots (2 X 2) = 4

In [100…

```
# Subplots structure
f,arr = plt.subplots(2,2,sharex=True,figsize=(15,15))

# Size of data (count of records) for Cluster number = 0
#c1_count = len(clust_prod[clust_prod['cluster']==0])

# Average number of records (customers) in each product category for Cluster number = 0
c0 = clust_prod[clust_prod['cluster']==0].drop('cluster',axis=1).mean()

# In subplot (# 0,0), plot Average number of customers in each product category in Clus
# Using bargraph
arr[0,0].bar(range(len(clust_prod.drop('cluster',axis=1).columns)),c0)

# Average number of records (customers) in each product category for Cluster number = 1
c1 = clust_prod[clust_prod['cluster']==1].drop('cluster',axis=1).mean()

# In subplot (# 0,1), plot Average number of customers in each product category in Clus
# Using bargraph
arr[0,1].bar(range(len(clust_prod.drop('cluster',axis=1).columns)),c1)

# Cluster 2
c2 = clust_prod[clust_prod['cluster']==2].drop('cluster',axis=1).mean()
arr[1,0].bar(range(len(clust_prod.drop('cluster',axis=1).columns)),c2)

# Cluster 3
c3 = clust_prod[clust_prod['cluster']==3].drop('cluster',axis=1).mean()
arr[1,1].bar(range(len(clust_prod.drop('cluster',axis=1).columns)),c3)

plt.show()
```



1. What are the top 10 items in each cluster?

In [163…

```
c0.nlargest(10)
#c1.nlargest(10)
#c2.nlargest(10)
#c3.nlargest(10)
```

Out[163…

```
aisle
fresh fruits                        0.485884
packaged vegetables fruits          0.311157
fresh vegetables                    0.301706
yogurt                              0.272677
water seltzer sparkling water       0.268381
milk                                0.225175
packaged cheese                     0.216890
chips pretzels                      0.201853
ice cream ice                       0.158218
soy lactosefree                     0.157543
dtype: float64
```

1. What are the top 10 items in all clusters combined?

To find this out, we combine all the cluser averages dataseries, group by their indicies keeping only the first occurances thereby eliminating the duplicates in the combined series, and finally keeping the top 10

In [147…

```
cp = c0.append(c1)
cp = cp.append(c2)
cp = cp.append(c3)
cp
# This obviously contains duplicates - indices could be the same, however averages may
```

Out[147…

```
aisle
air fresheners candles          0.008347
asian foods                     0.040015
baby accessories                0.002148
baby bath body care             0.002639
baby food formula               0.067203
                                  ...
trash bags liners               0.012523
vitamins supplements            0.025046
water seltzer sparkling water   0.414425
white wines                     0.004870
yogurt                          1.345083
Length: 536, dtype: float64
```

In [150…

```
cp = cp.groupby(cp.index).first()
```

1. cluster analysis confirms the initial hypothesis that below products are genereically bought by the majority of the customers.

In [159…

```
cp.nlargest(8)
```

Out[159…

```
aisle
fresh fruits                    0.485884
packaged vegetables fruits      0.311157
fresh vegetables                0.301706
yogurt                          0.272677
water seltzer sparkling water   0.268381
milk                            0.225175
packaged cheese                 0.216890
chips pretzels                  0.201853
dtype: float64
```

1. Let us inspect if the clusters differ in quantities and proportions, with respect to the product categories, or if a cluster is characterized by some goods not included in this list. For instance we can already see cluster 3 is most characterized by 'Fresh Fruits' whereas most of the other clusters are characterized by 'Fresh Vegetables'.

In [158…

```
from IPython.display import display, HTML
cluster_means = [[c0['fresh fruits'],c0['fresh vegetables'],c0['packaged vegetables fru
                 [c1['fresh fruits'],c1['fresh vegetables'],c1['packaged vegetables fru
                 [c2['fresh fruits'],c2['fresh vegetables'],c2['packaged vegetables fru
                 [c3['fresh fruits'],c3['fresh vegetables'],c3['packaged vegetables fru
cluster_means = pd.DataFrame(cluster_means, columns = ['fresh fruits','fresh vegetables
HTML(cluster_means.to_html())
```

Out[158…

	fresh fruits	fresh vegetables	packaged vegetables fruits	yogurt	packaged cheese	milk	water seltzer sparkling water	chips pretzels

	fresh fruits	fresh vegetables	packaged vegetables fruits	yogurt	packaged cheese	milk	water seltzer sparkling water	chips pretzels
0	0.485884	0.301706	0.311157	0.272677	0.216890	0.225175	0.268381	0.201853
1	4.998037	7.183513	2.247301	1.256133	0.971541	0.738960	0.410206	0.460255
2	1.430813	3.436757	0.991441	0.464574	0.476700	0.323348	0.251070	0.236091
3	3.415353	1.000232	1.110622	1.345083	0.603896	0.573284	0.414425	0.424397

In [164…

```
cluster_perc = cluster_means.iloc[:, :].apply(lambda x: (x / x.sum())*100,axis=1)
HTML(cluster_perc.to_html())
```

Out[164…

	fresh fruits	fresh vegetables	packaged vegetables fruits	yogurt	packaged cheese	milk	water seltzer sparkling water	chips pretzels
0	21.275967	13.211147	13.625003	11.940018	9.497192	9.859988	11.751901	8.838784
1	27.362596	39.327352	12.303229	6.876914	5.318863	4.045560	2.245742	2.519744
2	18.799788	45.156353	13.026772	6.104152	6.263472	4.248540	3.298866	3.102059
3	38.429623	11.254632	12.496738	15.134909	6.795052	6.450603	4.663118	4.775325

1. Above table depicts the percentage of these products with respect to the other top 8 in each cluster. We can see some interesting differences among the clusters.

- It seems that customers in cluster 2 buy more fresh vegetables than those in other clusters.
- Customers in cluster 3 buy more fresh fruits and yogurt than those in the other clusters.

Lets look at the 8th to 15th most bought products for each cluster. These will not include the generic products (i.e. vegetables, fruits, water, etc.) so we may find somthing interesting.

In [168…

```
c0.sort_values(ascending=False)[8:15]
```

Out[168…

```
aisle
ice cream ice      0.158218
soy lactosefree    0.157543
refrigerated       0.155701
soft drinks        0.147048
bread              0.141095
frozen meals       0.127470
crackers           0.124340
dtype: float64
```

In [169…

```
c1.sort_values(ascending=False)[8:15]
```

Out[169…

```
aisle
soy lactosefree                  0.582924
bread                            0.521099
chips pretzels                   0.460255
eggs                             0.439647
refrigerated                     0.420020
water seltzer sparkling water    0.410206
canned meals beans               0.393523
dtype: float64
```

In [170…

```
c2.sort_values(ascending=False)[8:15]
```

Out[170…
```
aisle
frozen produce                   0.290300
water seltzer sparkling water    0.251070
bread                            0.240846
chips pretzels                   0.236091
canned jarred vegetables         0.230861
eggs                             0.230385
soup broth bouillon              0.206847
dtype: float64
```

In [171…
```
c3.sort_values(ascending=False)[8:15]
```

Out[171…
```
aisle
bread                   0.374304
energy granola bars     0.368738
baby food formula       0.364332
soy lactosefree         0.364332
refrigerated            0.348794
crackers                0.283395
frozen produce          0.282236
dtype: float64
```

In [122…
```
'''

d0 = pd.DataFrame({'Products':c0.index, 'Averages':c0.values})
d0.sort_values('Averages', ascending=False)[0:10]

d1 = pd.DataFrame({'Products':c1.index, 'Averages':c1.values})
d1.sort_values('Averages', ascending=False)[0:10]

d2 = pd.DataFrame({'Products':c2.index, 'Averages':c2.values})
d2.sort_values('Averages', ascending=False)[0:10]

d3 = pd.DataFrame({'Products':c3.index, 'Averages':c3.values})
d3.sort_values('Averages', ascending=False)[0:10]

'''
```

Out[122…

	Products	Averages
50	fresh fruits	3.415353
133	yogurt	1.345083
98	packaged vegetables fruits	1.110622
53	fresh vegetables	1.000232
93	packaged cheese	0.603896
83	milk	0.573284
25	chips pretzels	0.424397
131	water seltzer sparkling water	0.414425
11	bread	0.374304
42	energy granola bars	0.368738