customer_segments

January 21, 2016

1 Creating Customer Segments

In this project you, will analyze a dataset containing annual spending amounts for internal structure, to understand the variation in the different types of customers that a wholesale distributor interacts with.

Instructions:

- Run each code block below by pressing **Shift+Enter**, making sure to implement any steps marked with a TODO.
- Answer each question in the space provided by editing the blocks labeled "Answer:".
- When you are done, submit the completed notebook (.ipynb) with all code blocks executed, as well as a .pdf version (File > Download as).

In [1]:
```
# Import libraries: NumPy, pandas, matplotlib
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

# Tell iPython to include plots inline in the notebook
%matplotlib inline

# Read dataset
data = pd.read_csv("wholesale-customers.csv")
print "Dataset has {} rows, {} columns".format(*data.shape)
print data.head()  # print the first 5 rows
```

```
Dataset has 440 rows, 6 columns
   Fresh  Milk  Grocery  Frozen  Detergents_Paper  Delicatessen
0  12669  9656     7561     214              2674          1338
1   7057  9810     9568    1762              3293          1776
2   6353  8808     7684    2405              3516          7844
3  13265  1196     4221    6404               507          1788
4  22615  5410     7198    3915              1777          5185
```

1.1 Feature Transformation

1) In this section you will be using PCA and ICA to start to understand the structure of the data. Before doing any computations, what do you think will show up in your computations? List one or two ideas for what might show up as the first PCA dimensions, or what type of vectors will show up as ICA dimensions.

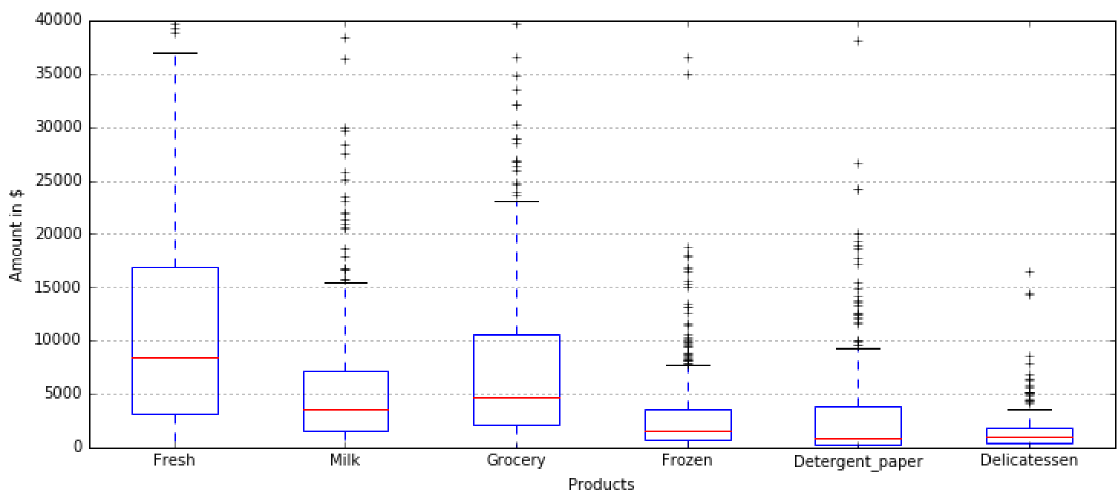
In [2]:
```
data.describe()
```

Out[2]:
```
                Fresh          Milk       Grocery        Frozen  \
count      440.000000    440.000000    440.000000    440.000000
mean     12000.297727   5796.265909   7951.277273   3071.931818
```

std	12647.328865	7380.377175	9503.162829	4854.673333
min	3.000000	55.000000	3.000000	25.000000
25%	3127.750000	1533.000000	2153.000000	742.250000
50%	8504.000000	3627.000000	4755.500000	1526.000000
75%	16933.750000	7190.250000	10655.750000	3554.250000
max	112151.000000	73498.000000	92780.000000	60869.000000

	Detergents_Paper	Delicatessen
count	440.000000	440.000000
mean	2881.493182	1524.870455
std	4767.854448	2820.105937
min	3.000000	3.000000
25%	256.750000	408.250000
50%	816.500000	965.500000
75%	3922.000000	1820.250000
max	40827.000000	47943.000000

In [3]:
```
fig, axes = plt.subplots(nrows=1, ncols=1, figsize=(12, 5))

# rectangular box plot
bplot1 = axes.boxplot(data.values,
                         vert=True,   # vertical box aligmnent
                         patch_artist=True)   # fill with color

axes.yaxis.grid(True)
axes.set_xlabel('Products')
axes.set_ylabel('Amount in $')

plt.setp(axes, xticks=[y+1 for y in range(len(data.columns))],
         xticklabels=['Fresh', 'Milk', 'Grocery', 'Frozen', 'Detergent_paper','Delicatessen'])

plt.ylim(0,40000);
```



PCA will use the features with more variance to build the first components. Given the 3rd line table above (std), We could expect that Fresh, Grocery and Milk will be highly important in the couple of first components.

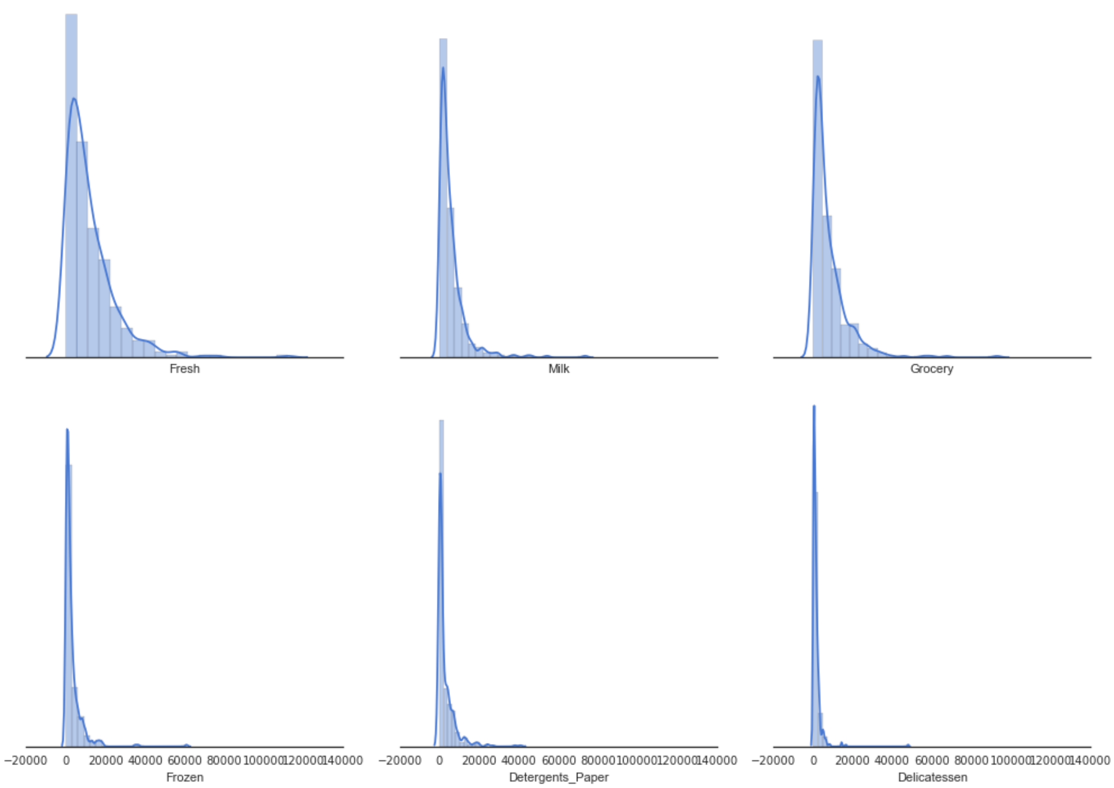
ICA will build independant components, to do so it needs features that best separate different groups.

The Detergent_paper feature is interesting : its 816 dollars median is low so to reach the 2881 dollars mean we need to have some large customer. Simalar statement can be made about the Frozen category.

Combining both of them could allow to clearly separate 2 groups with different purchasing behaviors.

```
In [4]: import seaborn as sns

        sns.set(style="white", palette="muted", color_codes=True)

        # Set up the matplotlib figure
        f, axes = plt.subplots(2, 3, figsize=(14, 10), sharex=True)
        sns.despine(left=True)


        # Plot a simple histogram with binsize determined automatically

        for i,col in enumerate(data.columns):
            if i < 3:
                nb = 0
            else:
                nb = 1
            sns.distplot(data[col], color="b", ax=axes[nb, i % 3], bins=20)
        #sns.distplot(data["Fresh"], color="b", ax=axes[0, 1])

        plt.setp(axes, yticks=[])
        plt.tight_layout()
```

```
/usr/local/lib/python2.7/site-packages/matplotlib/__init__.py:872: UserWarning: axes.color_cycle is depre
  warnings.warn(self.msg_depr % (key, alt_key))
```



```
In [5]: # TODO: Apply PCA with the same number of dimensions as variables in the dataset
        from sklearn.decomposition import PCA
        pca = PCA(n_components=6)
        pca.fit(data)

        # Print the components and the amount of variance in the data contained in each dimension
        print pca.components_
        print pca.explained_variance_ratio_
```

```
[[-0.97653685 -0.12118407 -0.06154039 -0.15236462  0.00705417 -0.06810471]
 [-0.11061386  0.51580216  0.76460638 -0.01872345  0.36535076  0.05707921]
 [-0.17855726  0.50988675 -0.27578088  0.71420037 -0.20440987  0.28321747]
 [-0.04187648 -0.64564047  0.37546049  0.64629232  0.14938013 -0.02039579]
 [ 0.015986    0.20323566 -0.1602915   0.22018612  0.20793016 -0.91707659]
 [-0.01576316  0.03349187  0.41093894 -0.01328898 -0.87128428 -0.26541687]]
[ 0.45961362  0.40517227  0.07003008  0.04402344  0.01502212  0.00613848]
```

2) How quickly does the variance drop off by dimension? If you were to use PCA on this dataset, how many dimensions would you choose for your analysis? Why?

The variance drops from 40% to 7% between the 2nd and the 3rd components. I would choose to keep only 2 dimensions. Since only 2 variables explains 85% of the variance, I can do some as simple as plotting the data points to think about how to group them.

3) What do the dimensions seem to represent? How can you use this information?

The first component has 70% of its weight on Fresh items. Buyers tend to differenciate through this items.

```
In [6]: print "Fresh items weight (or importance) is {0:.2f}%.".format(np.abs(pca.components_[0][0]) / r
```

```
Fresh items weight (or importance) is 70.42%.
```

The second component is mostly a mix of Milk and Grocery. We could name this category **"Grocery"**.

```
In [7]: print "Milk and Grocery items represent {0:.2f}% of the second component.".format( (np.abs(pca.c
```

```
Milk and Grocery items represent 69.88% of the second component.
```

Now all we are left with conceptuatually are 2 dimensions to rank our clients.

Removing the 4 PCA last dimensions enables us to group our customer in a 2 dimensional space with the added bonus of allowing us to visualize our groups more easily.

1.1.1 ICA

```
In [8]: # TODO: Fit an ICA model to the data
        # Note: Adjust the data to have center at the origin first!
        from sklearn.decomposition import FastICA
        from sklearn.preprocessing import StandardScaler

        data_centered = StandardScaler().fit_transform(data)


        ica_4 = FastICA(n_components=4, random_state=14).fit(data_centered)
        ica_6 = FastICA(n_components=6, random_state = 14).fit(data_centered)

        # Print the independent components
        print ica_4.components_
```

```
[[ 0.00305829  0.01303128  0.01935825  0.00244355  0.02027703 -0.00772317]
 [-0.04966602 -0.00018288 -0.00053902  0.00373094  0.00130949  0.0059979 ]
 [ 0.01090569  0.00235075 -0.00205501 -0.05424726 -0.00325838  0.01487577]
 [ 0.00553067 -0.01144728  0.00434874  0.0042735   0.00989897 -0.04633815]]
```

4) For each vector in the ICA decomposition, write a sentence or two explaining what sort of object or property it corresponds to. What could these components be used for?

```
In [9]: def min_weight(vect):
            w = np.min(vect) / vect[vect < 0].sum()
            return w * 100

        def max_weight(vect):
            w = np.max(vect) / vect[vect > 0].sum()
            return w * 100


        for i, v in enumerate(ica_4.components_):
            print "Component number {0}'s max is {2}, its value is {1:.4f}. It accounts for {3:.2f} % o
            print "Component number {0}'s min is {2} , its value is {1:.4f}. It accounts for {3:.2f} % 
            print " "
```

```
Component number 1's max is Detergents_Paper, its value is 0.0203. It accounts for 34.86 % of the positi
Component number 1's min is Delicatessen , its value is -0.0077. It accounts for 100.00 % of the negati

Component number 2's max is Delicatessen, its value is 0.0060. It accounts for 54.34 % of the positives
Component number 2's min is Fresh , its value is -0.0497. It accounts for 98.57 % of the negatives

Component number 3's max is Delicatessen, its value is 0.0149. It accounts for 52.88 % of the positives
Component number 3's min is Frozen , its value is -0.0542. It accounts for 91.08 % of the negatives

Component number 4's max is Detergents_Paper, its value is 0.0099. It accounts for 41.16 % of the positi
Component number 4's min is Delicatessen , its value is -0.0463. It accounts for 80.19 % of the negativ
```

With the statementents above, separates customers into groups with very distinct purchasing behaviors

- Component 1 : Customers who order Detergents_paper but also Milk and Grocery and don't order Delicatessen
- Component 2 : Customers who order Delicatessen and no Fresh products
- Component 3 : Customers who order Delicatessen and no Frozen products
- Component 4 : Customers who order Detergents_paper and no Delicatessen

Component 1 and 4 seems close enough. But if we look at the value. Component 1 is really about defining this group according to items it buys, component 4 is about customer who do not buy Delicattessen.

Interestingly the parameters used for a decomposition into 6 components uses different vectors.

ICA gives us an interstering way to explore the data graphically, it gives us insight on the combinaison of parameters that are worth trying first, since they are considered as being as closely independant as possible.

It comes to my mind that could make a good preprocessing step in case we were using a Naive Bayes Algorithm (I'm just saying this on the basis of intuition).

```
In [10]: for i, v in enumerate(ica_6.components_):
             print "Component number {0}'s max is {2}, its value is {1:.4f}. It accounts for {3:.2f} % 
             print "Component number {0}'s min is {2} , its value is {1:.4f}. It accounts for {3:.2f} %
             print " "
```

```
Component number 1's max is Milk, its value is 0.0723. It accounts for 78.76 % of the positives
Component number 1's min is Grocery , its value is -0.0565. It accounts for 75.26 % of the negatives

Component number 2's max is Detergents_Paper, its value is 0.0145. It accounts for 44.67 % of the positi
Component number 2's min is Grocery , its value is -0.0700. It accounts for 94.58 % of the negatives

Component number 3's max is Detergents_Paper, its value is 0.1332. It accounts for 83.45 % of the positi
Component number 3's min is Grocery , its value is -0.1084. It accounts for 85.18 % of the negatives

Component number 4's max is Delicatessen, its value is 0.0509. It accounts for 95.48 % of the positives
Component number 4's min is Grocery , its value is -0.0056. It accounts for 38.40 % of the negatives

Component number 5's max is Frozen, its value is 0.0541. It accounts for 88.05 % of the positives
Component number 5's min is Delicatessen , its value is -0.0168. It accounts for 53.68 % of the negativ

Component number 6's max is Fresh, its value is 0.0503. It accounts for 80.56 % of the positives
Component number 6's min is Grocery , its value is -0.0081. It accounts for 39.41 % of the negatives
```

1.2 Clustering

In this section you will choose either K Means clustering or Gaussian Mixed Models clustering, which implements expectation-maximization. Then you will sample elements from the clusters to understand their significance.

1.2.1 Choose a Cluster Type

5) What are the advantages of using K Means clustering or Gaussian Mixture Models?

According to scikit learn : "One can think of mixture models as generalizing k-means clustering to incorporate information about the covariance structure of the data as well as the centers of the latent Gaussians."

Gaussian Mixture Model is a probabilistic wheras K-Means minimizes the distance between the centroids and the data points.

Gaussian Mixture Model allows us to draw much more complicated boundaries between clusters of points which can be very interesing to separate the clusters when lines cannot capture properly what differentiate data points.

K-means none is much simpler to understand and it is sometimes armful to choose unecessary complexity.

In our case, we want to be able to explain our data as simply as possible, hence choosing the K-Means approach.

6) Below is some starter code to help you visualize some cluster data. The visualization is based on this demo from the sklearn documentation.

In [11]:
```
# Import clustering modules
from sklearn.cluster import KMeans
from sklearn.mixture import GMM
```

In [12]:
```
# TODO: First we reduce the data to two dimensions using PCA to capture variation


reduced_data = PCA(n_components=2).fit_transform(data)

reduced_data = StandardScaler().fit_transform(reduced_data)

print reduced_data[:10]  # print upto 10 elements
```

```
[[-0.05066239  0.13161505]
 [ 0.34502287  0.33556674]
```

```
 [ 0.37738285  0.21406486]
 [-0.07718708 -0.5212911 ]
 [-0.83067886 -0.17928035]
 [ 0.2155776  -0.07967954]
 [ 0.05576966 -0.16710073]
 [ 0.34874672  0.11866355]
 [ 0.52313722 -0.18311407]
 [ 0.37595155  1.11903068]]
```

In [13]:
```
#clusters = GMM(n_components=3, covariance_type='spherical').fit(reduced_data)
#print clusters
```

In [14]:
```
# TODO: Implement your clustering algorithm here, and fit it to the reduced data for visualiza
# The visualizer below assumes your clustering object is named 'clusters'
def fit_k_mean(n_clusters):
    clusters = KMeans(n_clusters).fit(reduced_data)
    return clusters
```

In [15]:
```
from sklearn import metrics
def compute_sihouette(n_clusters,clusters):
    labels = clusters.labels_
    print "for {0} clusters silhouette score is {1}".format(n_clusters,metrics.silhouette_score
```

In [16]:
```
def plot_clusters(clusters, reduced_data):
    # Plot the decision boundary by building a mesh grid to populate a graph.
    x_min, x_max = reduced_data[:, 0].min() - 1, reduced_data[:, 0].max() + 1
    y_min, y_max = reduced_data[:, 1].min() - 1, reduced_data[:, 1].max() + 1
    hx = (x_max-x_min)/1000.
    hy = (y_max-y_min)/1000.
    xx, yy = np.meshgrid(np.arange(x_min, x_max, hx), np.arange(y_min, y_max, hy))

    # Obtain labels for each point in mesh. Use last trained model.
    Z = clusters.predict(np.c_[xx.ravel(), yy.ravel()])

    centroids = clusters.cluster_centers_


    # Put the result into a color plot

    Z = Z.reshape(xx.shape)
    plt.figure(1)
    plt.clf()
    plt.imshow(Z, interpolation='nearest',
               extent=(xx.min(), xx.max(), yy.min(), yy.max()),
               cmap=plt.cm.Paired,
               aspect='auto', origin='lower')

    plt.plot(reduced_data[:, 0], reduced_data[:, 1], 'k.', markersize=2)
    plt.scatter(centroids[:, 0], centroids[:, 1],
                marker='x', s=169, linewidths=3,
                color='w', zorder=10)
    plt.title('Clustering on the wholesale grocery dataset (PCA-reduced data)\n'
              'Centroids are marked with white cross')
    plt.xlim(x_min, x_max)
    plt.ylim(y_min, y_max)
```

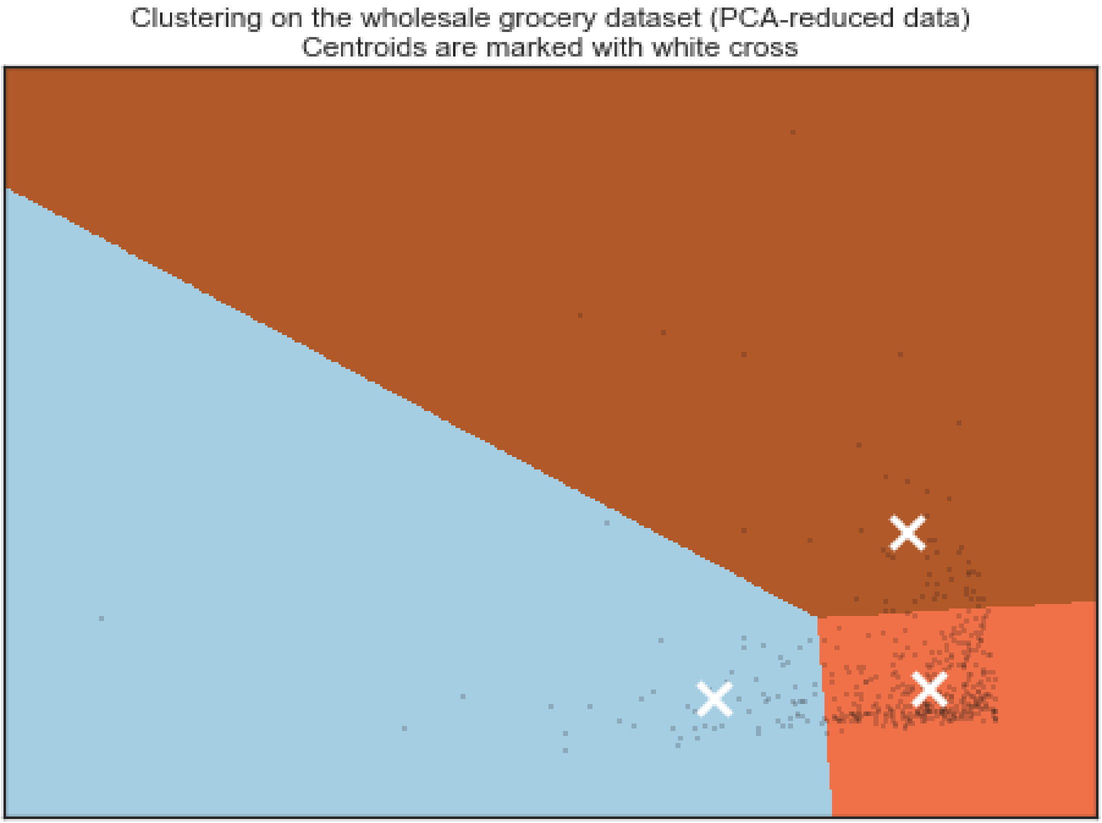
```
            plt.xticks(())
            plt.yticks(())
            plt.show()
```

```
In [17]: def run_k_means(n_clusters):
             clusters = fit_k_mean(n_clusters)
             compute_silhouette(n_clusters, clusters)
             plot_clusters(clusters,reduced_data)
```

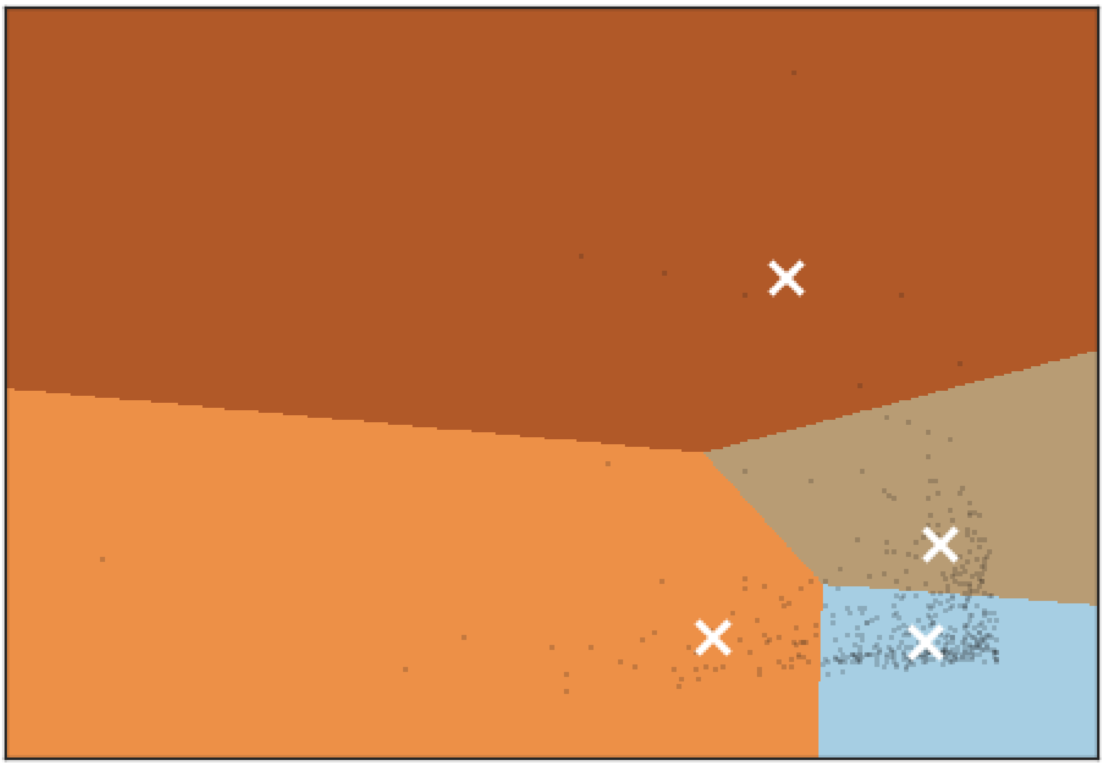
```
In [18]: for i in range(2,5,1):
             run_k_means(n_clusters=i)
```

```
for 2 clusters silhouette score is 0.533707466358
```


```
for 3 clusters silhouette score is 0.523070794792
```




```
for 4 clusters silhouette score is 0.470192829698
```



I selected 3 clusters with 2 clusters only we cannot account for customers who who order a lot of Grocery and Milk.

With 4 clusters or more we are left with categories with very few points.

7) What are the central objects in each cluster? Describe them as customers.

The central objects are the centroids. They represent the average location of the points located in their cluster.

The left cluster is made of **premium customers who order a lot more fresh products**.

the top cluster is made of **premium customers who order Grocery (and Milk)**

The right bottom dense cluster order comparatively low quantities of those.

1.2.2 Conclusions

** 8)** Which of these techniques did you feel gave you the most insight into the data?

The variance in the data being quite important, PCA resulted in being powerful approach to be able to limit the number of dimensions used.

KMeans came as a nice complement to draw a line between clusters and effectitvely deciding on our segments.

9) How would you use that technique to help the company design new experiments?

Instead of conducting the change in delivery method across the whole population of customer, the change could be tested taking into account our 3 customers segments.

We would randomly split each customer segment in 2 folds : a control group and a test group.

2 weeks after the change, we would measure customer statisfaction via a survey.

Comparing our control and test groups we would be in a position to implement the change only for some customer segment.

10) How would you use that data to help you predict future customer needs?

To enable the company the choose the best delivery for new customers, we ask them their estimated volume of purchase for each category.

We could transform this information according into our PCA-reduced data, see in which customer segment this new customer falls and at last choose accordinly the delivery method.