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
import seaborn as sns

import warnings

warnings.filterwarnings('ignore')

# 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

data.describe()
```

```
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
```

Out[1]:

	Fresh	Milk	Grocery	Frozen	Detergents_Paper
count	440.000000	440.000000	440.000000	440.000000	440.000000
mean	12000.297727	5796.265909	7951.277273	3071.931818	2881.493182
std	12647.328865	7380.377175	9503.162829	4854.673333	4767.854448
min	3.000000	55.000000	3.000000	25.000000	3.000000
25%	3127.750000	1533.000000	2153.000000	742.250000	256.750000
50%	8504.000000	3627.000000	4755.500000	1526.000000	816.500000
75%	16933.750000	7190.250000	10655.750000	3554.250000	3922.000000
max	112151.000000	73498.000000	92780.000000	60869.000000	40827.000000

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.

Answer: We can expect that PCA will detect primary and secondary vectors that explains the data variace. Data will probably be explained in just first two dimmensions. By using PCA we will be able to reduce these 6 variables to just the two of them that best captures that information. By having smaller number of dimmensions we will be able to visulize the data better.

Based on Standard Diveation of the values Fresh column has highers value followed by grocery and Milk. The Primary vector will be composed based on this variation.

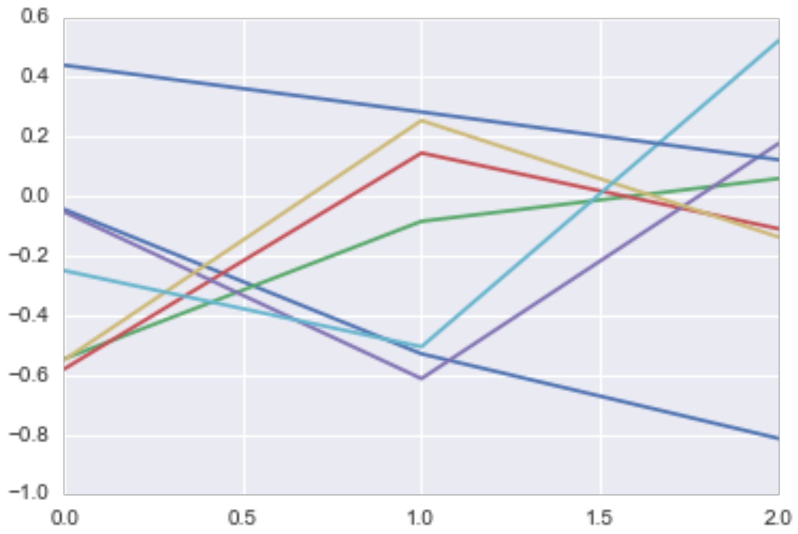
ICA will find vectors which are statisticly separate from eachother by "whitnening" the overlap in data and separating each vector into a separate signal.

In [2]:
```
from sklearn import preprocessing
stnd = preprocessing.StandardScaler()
data_stnd = stnd.fit_transform(data)
```

PCA

In [3]:
```
# TODO: Apply PCA with the same number of dimensions as variables in t
he dataset
from sklearn.decomposition import PCA
pca = pca = PCA(n_components=3)


pca.fit(data_stnd)
pca_dt = pca.transform(data_stnd)

pca_df = pd.DataFrame(pca_dt , columns=['PC1','PC2', 'PC3'])


# Print the components and the amount of variance in the data containe
d in each dimension
#print 'components_', pca.components_
print 'explained_variance_ratio_', pca.explained_variance_ratio_
print plt.plot(pca.components_)
print plt.plot(pca.explained_variance_ratio_)
#plt.legend()
```

```
explained_variance_ratio_ [ 0.44082893  0.283764    0.12334413]
[<matplotlib.lines.Line2D object at 0x10b428fd0>, <matplotlib.lines.
Line2D object at 0x10b439290>, <matplotlib.lines.Line2D object at 0x
10b4394d0>, <matplotlib.lines.Line2D object at 0x10b439690>, <matplo
tlib.lines.Line2D object at 0x10b439850>, <matplotlib.lines.Line2D o
bject at 0x10b439a10>]
[<matplotlib.lines.Line2D object at 0x10b2dd050>]
```



To interpret each component, we must compute the correlations between the original data for each variable and each principal component.

These correlations are obtained using the correlation procedure. In the variable statement we will include the first three principal components, PC1, PC2, and PC3, in addition to all six of the original variables. We will use these correlations between the principal components and the original variables to interpret these principal components.

Because of standardization, all principal components will have mean 0. The standard deviation is also given for each of the components and these will be the square root of the eigenvalue.

We want to examine correlations between Principal components and the origianal values.

To interpret principal components we look at which variables are most strongly correlated to each other (which number are large in magnitude - furthest from zero in either direction)

Here a correlation value above +-0.5 is deemed important.

PC1

The first principal componnent is strongly correlated to 3 of the 6 original variables. The first principal component decreases with Milk, Detergent & Paper and Grocery. This suggest that these 3 categories varry together.

This component can be viewed as retailers intrest in Milk, Detergent & Paper and Grocery

PC2

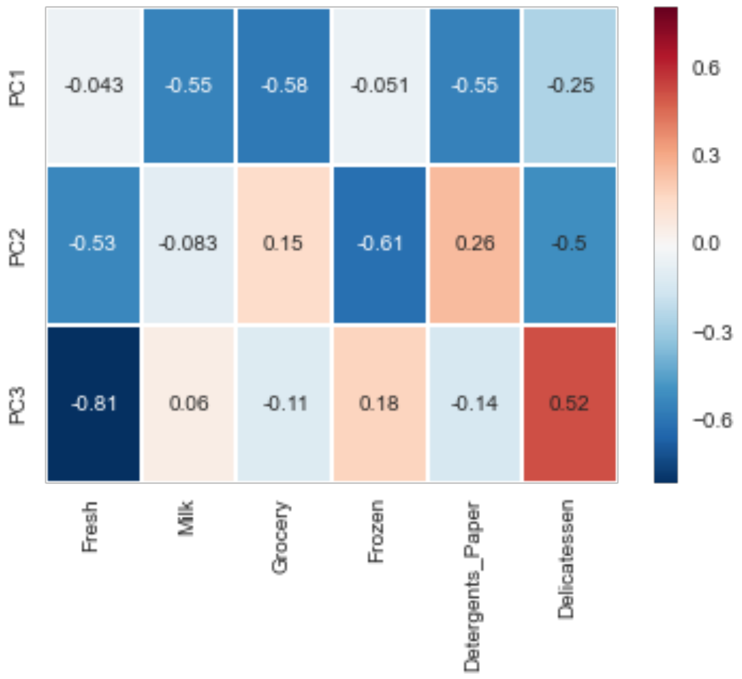
The second Principal Component decreases with Delicatesen Fresh, Frozen and Frozen.

PC3

Is made up from Delicatesen and on the oposit side fresh.

```
In [4]: pca_correlations = pd.DataFrame(pca.components_, columns=data.columns,
        index=['PC1','PC2', 'PC3'])

        sns.heatmap(pca_correlations,  annot=True)
```

```
Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0x10b48ba50>
```



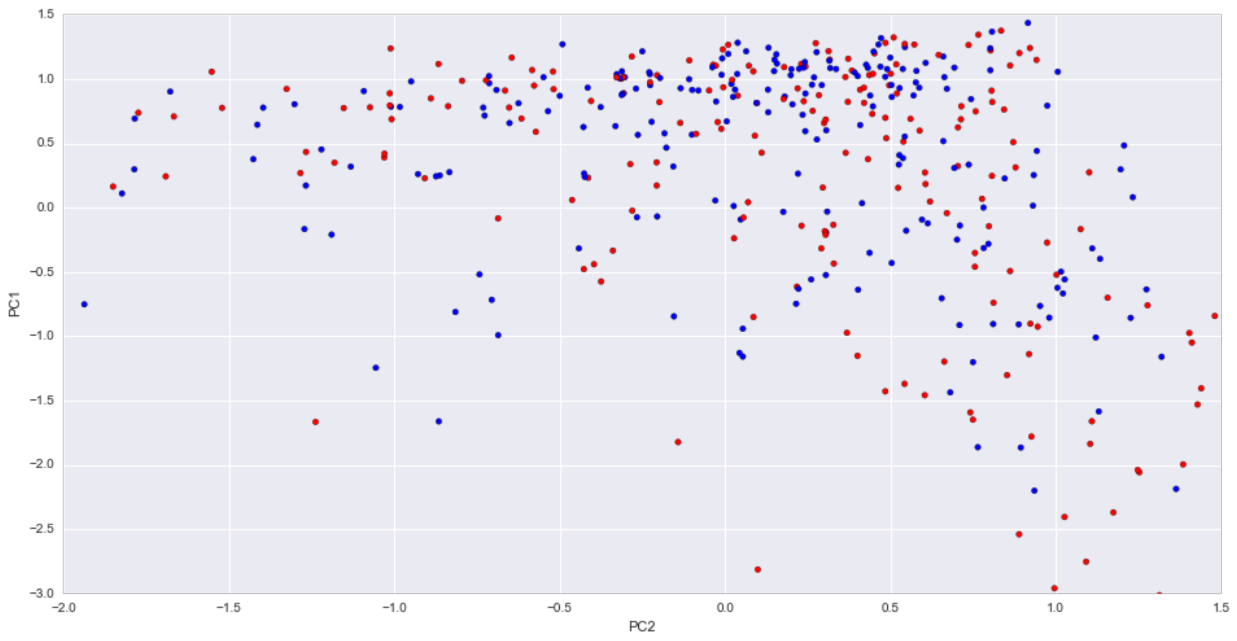
2) How quickly does the variance drop off by dimension? If you were to use PCA on this dataset, how many dimensions would you choose for your analysis? Why?

Answer: We see that the first PC already explains 44% of the variance, while the second one accounts for another 28% for a total of almost 72% between the two of them. Third dimmension is responisble for 12% for 84%.

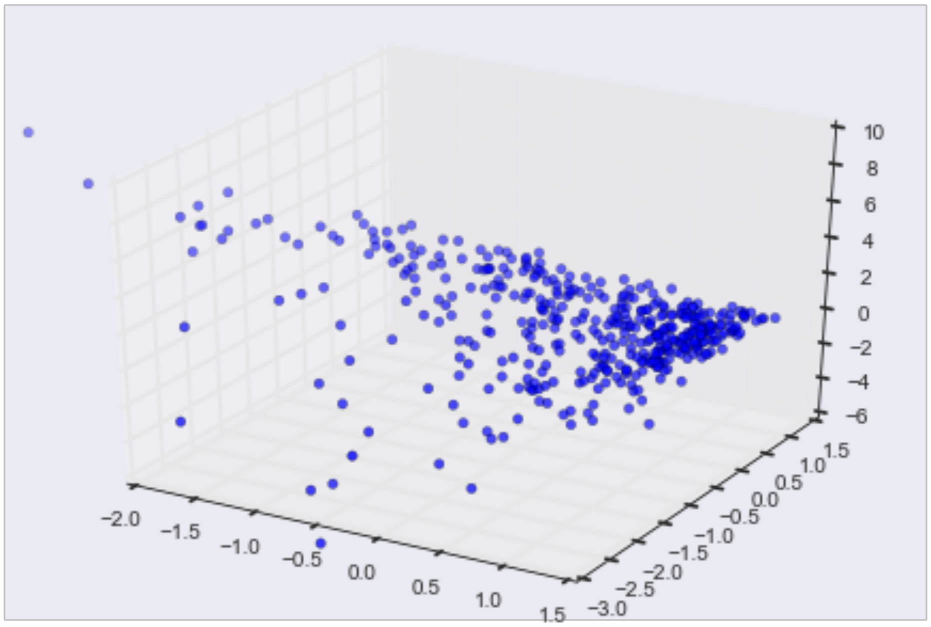
I am going to choose 3 dimmensions for my anlyses as they explain 88% of variance.

In [5]:
```
ax = pca_df.plot(kind='scatter', x='PC2', y='PC1', figsize=(16,8), c=[
'b', 'r'], marker=u'o')
ax.set_xlim (-2, 1.5)
ax.set_ylim (-3, 1.5)

# most of the variance is along the PC1 exis
```

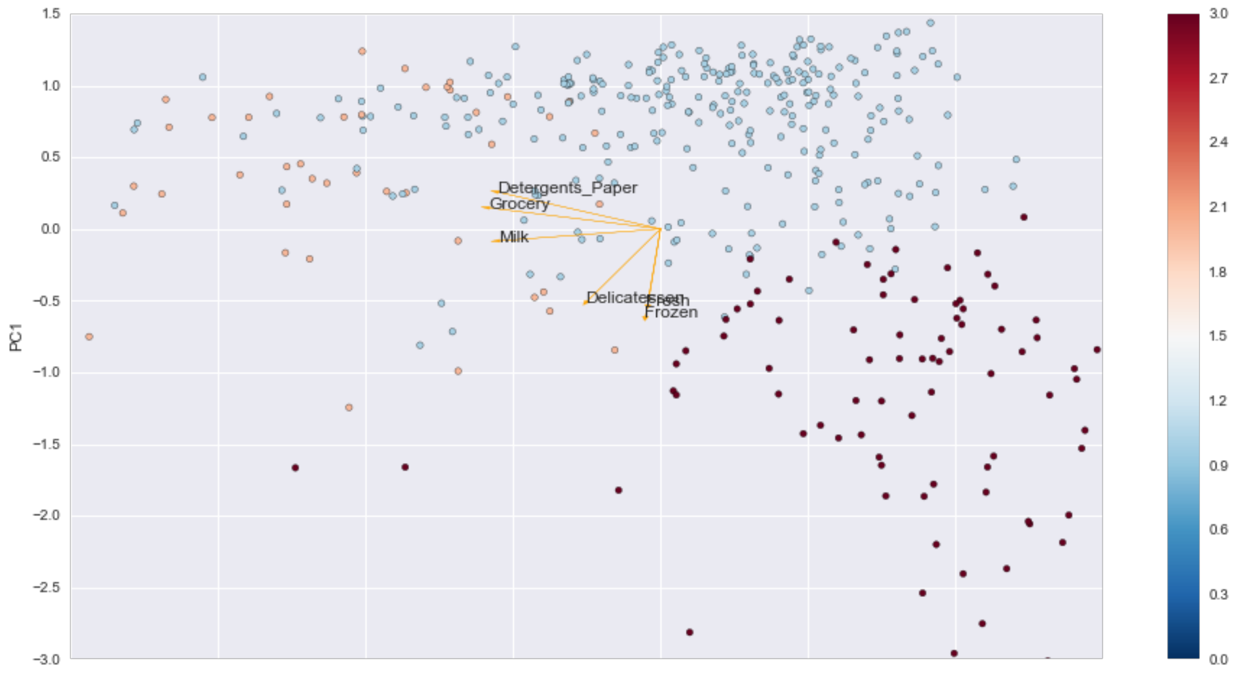
Out[5]:
```
(-3, 1.5)
```



In [6]:
```
#attempting to make 3D plot with our 3 variables

from matplotlib import pyplot
import pylab
from mpl_toolkits.mplot3d import Axes3D
import random


fig = pylab.figure()
ax = Axes3D(fig)




ax.scatter(pca_df.PC1, pca_df.PC2, pca_df.PC3, c=['b', 'r'], marker='o
', )

ax.set_xlim (-2, 1.5)
ax.set_ylim (-3, 1.5)




pyplot.show()
```



In [7]:
```
from sklearn.cluster import KMeans

df = pd.DataFrame(data_stnd, columns=['Fresh',  'Milk' , 'Grocery'  ,'
Frozen' , 'Detergents_Paper' , 'Delicatessen'])

kmeans = KMeans(n_clusters=4)
clusters = kmeans.fit(data)

pca_df['cluster'] = pd.Series(clusters.labels_, index=pca_df.index)

ax = pca_df.plot(
        kind='scatter',
        x='PC2',y='PC1',
        c=pca_df.cluster.astype(np.float),
        colormap = 'RdBu_r',
        figsize=(16,8),
        xlim = [-2, 1.5],
        ylim = [-3, 1.5]   )

for i, (pc1, pc2) in enumerate(zip(pca.components_[0], pca.components_
[1])):
        ax.arrow(0, 0, pc1, pc2, width=0.001, fc='orange', ec='orange'
)
        ax.annotate(df.columns[i], (pc1, pc2), size=12)
```



In [ ]:
```
pca_df['cluster'].plot(kind='hist')
```

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

Answer: After applying PCA I have applied clustering. Fine tuning the number of clusters parameters, I can observe that the data is separted in four different clusters. Majority of the custores are in the Detergent_Paper and Grocery

First two Dimmensions of PCA are two dimmensions that explain majority (86%) of variance in data. This is done by combining information from number of different original dimmensions to produce new dimmensions. We can use this new dimmensions to represent the data in further machine learning algoritams, having advantage that we have reduced dimmensionality.

From Above biplot we can see that customers can be grouped in 3-4 groups.

Detergent_Paper and Grocery Milk Delicatessen Frozen

The First Component places approximatly equal weight to Detergent_Paper and Grocery Milk and much less weight to Delicatessen and Frozen

The second component places most of its weight on Delicatessen & Frozen

From this we can see that Detergent_Paper, Grocery and Milk are correlated to each other while Delicatesen and Frozen are in a category of their own.

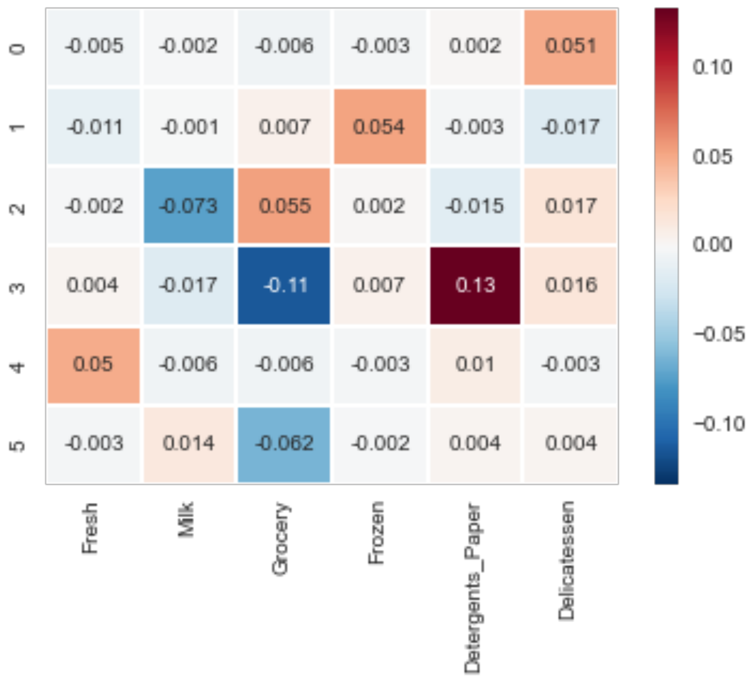
By examining the differences between the customers via two principal components. Vectors suggest that Customers with high demand for Detergent / paper / Grocery and milk have little demand for frozen and about 25% of demand for Delicatessen

We can use PCA componenets to visualize the data in two dimmension while retaining most of the charatersitic of the original data.

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 import preprocessing


ica = FastICA()

stnd = preprocessing.StandardScaler()
ica_scale = preprocessing.StandardScaler()
ica_data = stnd.fit_transform(data_stnd)


S_ = ica.fit_transform(data_stnd)
A_ = ica.mixing_


assert np.allclose(ica_data, np.dot(S_, A_.T) + ica.mean_)


ica_data= pd.DataFrame(ica.components_,columns=data.columns).round(3)
sns.heatmap(ica_data, annot=True)
```

Out[8]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x10b7817d0>
```



	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	-0.005	-0.002	-0.006	-0.003	0.002	0.051
1	-0.011	-0.001	0.007	0.054	-0.003	-0.017
2	-0.002	-0.073	0.055	0.002	-0.015	0.017
3	0.004	-0.017	-0.11	0.007	0.13	0.016
4	0.05	-0.006	-0.006	-0.003	0.01	-0.003
5	-0.003	0.014	-0.062	-0.002	0.004	0.004

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?

From the heat map above we will examine how each of the origianl componnetnts relate to recovered data trhough ICA.

Fresh has highest simillarity to Component 1 Milk is most simillar to components 0 and 2 Grocery has highest simillarity to Component 5 Frozen has highest simillarity to Component 4 Detergent_paper has highest simillarity to Component 5 and Delicatesen has highest simillarity to Component 3

These componenets can be used to reduce the feature set into new ones that are statistically independent from one another.

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.

Choose a Cluster Type

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

Answer: Advantages of K Means clustering:

- With a large number of variables, K-Means may be computationally faster than hierarchical clustering (if K is small).
- K-Means may produce tighter clusters than hierarchical clustering, especially if the clusters are globular.

Advantages of Gaussian Mixture Models:

- It is the fastest algorithm for learning mixture models
- The GMM algorithm is a good algorithm to use for the classification of static postures and non-temporal pattern recognition.

Comparison of the K-means algorithm with the EM algorithm for Gaussian mixtures shows that there is a close similarity. Whereas the K-means algorithm performs a hard assignment of data points to clusters, in which each data point is associated uniquely with one cluster, the EM algorithm makes a soft assignment based on the posterior probabilities.

6) Below is some starter code to help you visualize some cluster data. The visualization is based on this demo (http://scikit-learn.org/stable/auto_examples/cluster/plot_kmeans_digits.html) from the sklearn documentation.

In [9]:
```
# Import clustering modules
from sklearn.cluster import KMeans
from sklearn.mixture import GMM
```

In [10]:
```
# TODO: First we reduce the data to two dimensions using PCA to captur
e variation
reduced_data = pca_df[['PC1', 'PC2']]
print reduced_data[:10]  # print upto 10 elements
```

```
        PC1       PC2
0 -0.193291  0.305100
1 -0.434420  0.328413
2 -0.811143 -0.815096
3  0.778648 -0.652754
4 -0.166287 -1.271434
5  0.156170  0.295141
6  0.335288  0.525003
7 -0.140586  0.230993
8  0.517320  0.659363
9 -1.592109  0.741011
```

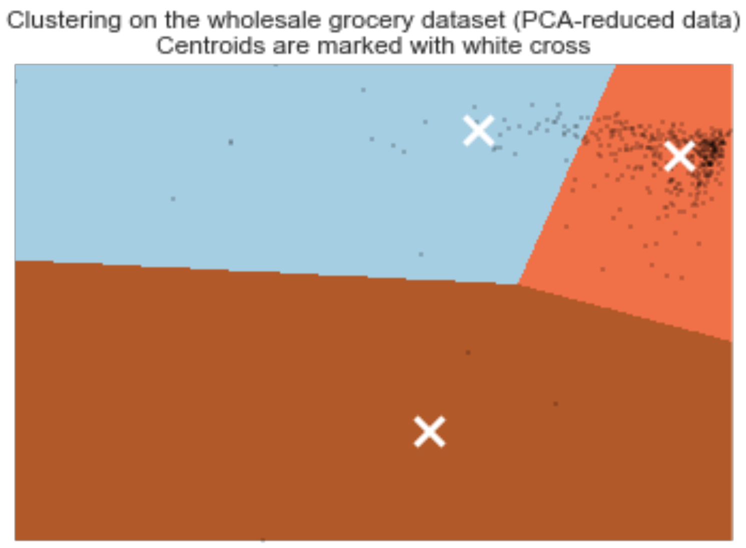
In [11]:
```
# TODO: Implement your clustering algorithm here, and fit it to the re
duced data for visualization
# The visualizer below assumes your clustering object is named 'cluste
rs'

clusters = KMeans(n_clusters=3)
clusters.fit(reduced_data)



print clusters
```

```
KMeans(copy_x=True, init='k-means++', max_iter=300, n_clusters=3, n_
init=10,
    n_jobs=1, precompute_distances='auto', random_state=None, tol=0.
0001,
    verbose=0)
```

In [12]:
```
# Plot the decision boundary by building a mesh grid to populate a gra
ph.
x_min, x_max = reduced_data['PC1'].min() , reduced_data['PC1'].max()
y_min, y_max = reduced_data['PC2'].min() , reduced_data['PC2'].max()
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_m
ax, hy))

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

In [13]:
```
# TODO: Find the centroids for KMeans or the cluster means for GMM

centroids = clusters.cluster_centers_
#print centroids
```

In [14]:
```
# 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['PC1'], reduced_data['PC2'], '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 da
ta)\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 [15]:
```
#TODO: Implement your clustering algorithm here, and fit it to the red
uced data for visualization
# The visualizer below assumes your clustering object is named 'cluste
rs'

clusters = GMM(n_components=3).fit(reduced_data)
# clusters = GMM(n_components=3).fit(reduced_data)
# clusters = KMeans(n_clusters=2).fit(reduced_data)
# clusters = KMeans(n_clusters=3).fit(reduced_data)
print clusters
```

```
GMM(covariance_type='diag', init_params='wmc', min_covar=0.001,
  n_components=3, n_init=1, n_iter=100, params='wmc', random_state=N
one,
  thresh=None, tol=0.001)
```

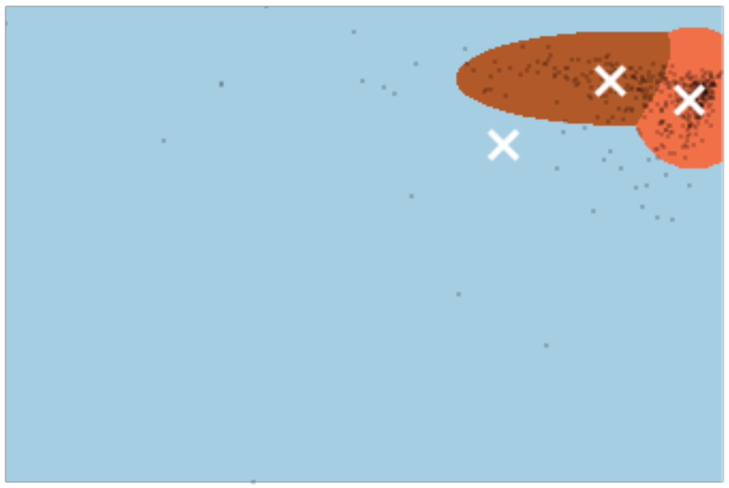
In [16]:
```
# Plot the decision boundary by building a mesh grid to populate a gra
ph.
x_min, x_max = reduced_data['PC1'].min() , reduced_data['PC1'].max()
y_min, y_max = reduced_data['PC2'].min() , reduced_data['PC2'].max()
hx = (x_max-x_min)/1000.
hy = (y_max-y_min)/1000.
xx, yy = np.meshgrid(np.arange(x_min, x_max, hx), np.arange(y_min, y_m
ax, hy))

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

In [17]:
```
# TODO: Find the centroids for KMeans or the cluster means for GMM

centroids = clusters.means_
# centroids = clusters.cluster_centers_
print centroids
```

```
[[-2.87924272 -1.70246154]
 [ 0.81499208 -0.09020858]
 [-0.73775307  0.63075796]]
```

In [18]:
```
# 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['PC1'], reduced_data['PC2'], '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 da
ta)\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()
```

Clustering on the wholesale grocery dataset (PCA-reduced data)
Centroids are marked with white cross



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

Answer: From PCA we idntified 4 grouping / correlations and I used this value as K . We can see that certain our customers can be devided in 4 such goroups as well.

Majority of the customers are in tow top right clusters.

Conclusions

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

Answer: PCA gave me most insight by enabling visulization of the customers in addition to KMeans clustering where I was able to assing clustes to individual customers. Overall I found that Gaussian Mixture Model (GMM) provides more logical clustering of the data as Kmeans wasn't able to find a clear devide in the clusters.

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

Answer: We could use results of PCA as input parameters in regression, or other types of clusters. Having the abilty to cluster the customers we can treat them as groups of customers on which we can apply different experiments. Such as trying to preidct how would spending change if demand for one of the groups of products is changed.

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

Answer: By seeing what type of products customers are intersted and this can influence how we interact with them.

Refernces: K-Means Clustering Overview - http://www.improvedoutcomes.com/docs/WebSiteDocs/Clustering/K-Means_Clustering_Overview.htm (http://www.improvedoutcomes.com/docs/WebSiteDocs/Clustering/K-Means_Clustering_Overview.htm)