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 [4]:
```
# 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
```

##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: PCA measures the direction of maximum variance, so the components with the highest variance will likely show up as the first PCA dimensions. Those components are: Fresh, Milk, and Groccery.

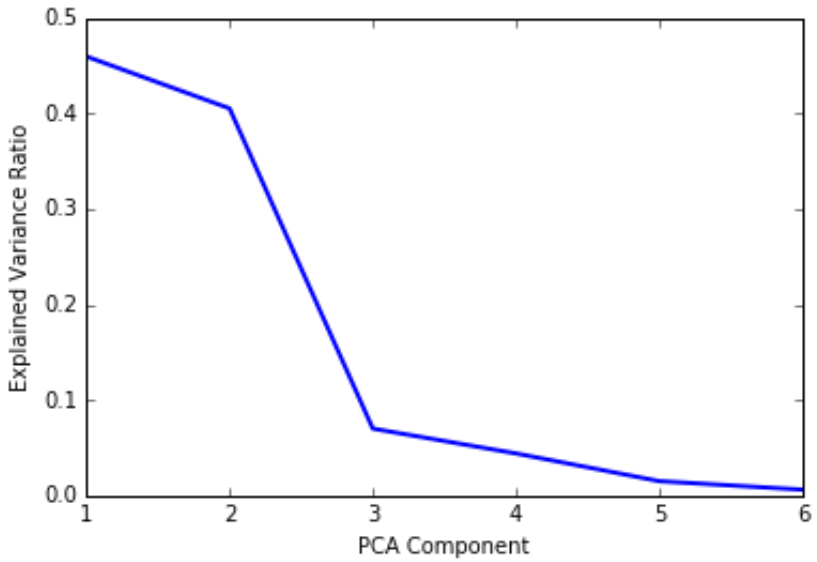
(Although we can probably infer by the considerably higher magnitude of the components in those 3 columns that their variance will be higher than the rest, I've verified this assertion by manually calculating the variance myself.)

ICA, on the other hand, is used to separate a signal into its independent and distinct sources. In this case, our "signal" is the data consisting of how much of each good a customer or business bought from the supplier and the "source" is a customer segment or business sector that tends to purchase each product in very distinct patterns (i.e. lots of Fresh, little Frozen, little Grocery.)

###PCA

In [94]:
```
# TODO: Apply PCA with the same number of dimensions as variables in the dat
from sklearn.decomposition import PCA
pca = PCA(n_components=6)
pca.fit(data)
plt.figure(2)
plt.plot([1, 2, 3, 4, 5, 6],pca.explained_variance_ratio_,lw=2)
plt.xlabel("PCA Component")
plt.ylabel("Explained Variance Ratio")
# Print the components and the amount of variance in the data contained in e
print pca.components_
print pca.explained_variance_ratio_
```

```
[[-0.97653685 -0.12118407 -0.06154039 -0.15236462  0.00705417 -0.0681047
1]
 [-0.11061386  0.51580216  0.76460638 -0.01872345  0.36535076  0.0570792
1]
 [-0.17855726  0.50988675 -0.27578088  0.71420037 -0.20440987  0.2832174
7]
 [-0.04187648 -0.64564047  0.37546049  0.64629232  0.14938013 -0.0203957
9]
 [ 0.015986    0.20323566 -0.1602915   0.22018612  0.20793016 -0.9170765
9]
 [-0.01576316  0.03349187  0.41093894 -0.01328898 -0.87128428 -0.2654168
7]]
[ 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?

Answer: The first 2 dimensions account for nearly 86% of all of the variance (46% and 40% respectively) and suddenly drops of to 7% and 4% for the 3rd and 4th components. It makes sense to use only the first 2 dimensions and only maybe try again with the 3rd dimension added back if the analysis using only the first 2 dimensions ends up unsatisfactory.

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

Answer: The first dimension has a highly negative correlation (-0.98) with the first variable: Fresh. This dimension represents a measure of how little one is spending on Fresh produce. It also signifies that spending on Fresh produce is relatively uncorrelated with the other 5 goods (further confirmed by the fact that the entries corresponding to Fresh in the other 5 PCA vectors are close to 0.)

The second dimension has moderately high correlations with the 2nd and 3rd variables: Milk and Grocery. This dimension represents a measure of how much one is spending on Milk and Grocery. PCA has determined that a significant correlation exists between spending on Milk and Grocery and has decided to combine those two into a single dimension, simplifying our data. This makes sense since Milk products and Grocery products are often used together to make certain foods like sandwiches, desserts, etc.

###ICA

In [114]:
```
# TODO: Fit an ICA model to the data
# Note: Adjust the data to have center at the origin first!
from sklearn.decomposition import FastICA
ica = FastICA()
from sklearn.preprocessing import StandardScaler
myscaler = StandardScaler()
data2 = myscaler.fit_transform(data)
ica.fit(data2)
components2 = 1000*ica.components_
print "Transformed ICA matrix: \n"
print components2.astype(int)
print "\nOriginal ICA matrix:\n"
# Print the independent components
print ica.components_
```

```
Transformed ICA matrix:

[[ -10   -1    8   54   -2  -16]
 [  -2   51  -48   -3  -23   -9]
 [  -4  -55   24    0  -19   15]
 [  -4   -2   -5   -2    2   51]
 [  50   -6   -4   -3    7   -2]
 [  -3    7  129   -6 -132  -15]]

Original ICA matrix:

[[-0.01088055 -0.00142686  0.0082333   0.0540615  -0.00285914 -0.0167320
6]
 [-0.00283332  0.05145475 -0.04880457 -0.00375662 -0.02314896 -0.0094299
3]
 [-0.00428649 -0.05510768  0.02425562  0.00036868 -0.01928228  0.0150948
2]
 [-0.00490364 -0.00232737 -0.0057128  -0.00257291  0.00210924  0.0512138
1]
 [ 0.05008524 -0.00697749 -0.00432336 -0.00343211  0.00754314 -0.0028996
5]
 [-0.00373097  0.00732033  0.12999569 -0.00637638 -0.13206548 -0.0150920
5]]
```

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?

Answer: We'll refer to the following transformed ICA matrix for our analysis: [[4 2 5 2 -2 -51] [50 -6 -6 -3 10 -2] [-3 17 111 -7 -133 -16] [2 -13 66 1 -10 -4] [2 72 -55 -1 16 -16] [-10 0 7 54 -2 -16]]

The first vector, [4 2 5 2 -2 -51], refers to a business that spends roughly average on everything except Delicatssen items. If we multiply it by -1, we get [-4 -2 -5 -2 2 51] which indicates roughly average spending on most items but above average spending on Delicatssen. This probably corresponds to a Deli or Sandwich shop.

The second vector, [50 -6 -6 -3 10 -2], refers to a business that spends a disproportionate amount in Fresh produce and a little more than average on Detergents and Paper. The only type of business that somewhat fits this is a farmer's market store.

The third vector, [-3 17 111 -7 -133 -16], refers to a business that spends a lot more than average on groceries and a lot less than average on Detergents and Paper products. If we multiply it by -1, we get [3 -17 -111 7 133 16], a business that spends a lot on detergents and little on groceries. A hotel might fit this.

The fourth vector, [2 -13 66 1 -10 -4], corresponds to a business that spends a lot more on Groceries than everything else. This is likely a grocery store.

The fifth vector, [2 72 -55 -1 16 -16], corresponds to a business that buys a disproportionate amount of Milk products and very little Grocery products. This looks like a cheese maker.

The sixth vector, [-10 0 7 54 -2 -16], corresponds to a business that buys a ton of frozen foods. This is likely a convenience store.

These vectors could be used to explore possible customer segmentations and the real-world business that the particular segmentation might correspond to (like I've suggested above.)

##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: K-Means clustering scales well to very large sample sizes. Gaussian Mixture Models work well for density estimation and is preferable over K-means for larger #'s of clusters.

Note: I initially tried using 2 clusters and found the overall shape of the plot to naturally lend itself to 3 clusters so I revised it to 3. Since 3 clusters is relatively small, I decided to go with K-Means which is optimal for small numbers of clusters.

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 [50]:
```
# Import clustering modules
from sklearn.cluster import KMeans
from sklearn.mixture import GMM
```

In [112]:
```
# TODO: First we reduce the data to two dimensions using PCA to capture vari
pca2 = PCA(n_components = 2)
reduced_data = pca2.fit_transform(data)
print "Our PCA vectors (for reference again):\n"
print pca2.fit(data).components_
print "\n1st 10 elements of our reduced data:\n"
print reduced_data[:10]  # print upto 10 elements
```

```
Our PCA vectors (for reference again):

[[-0.97653685 -0.12118407 -0.06154039 -0.15236462  0.00705417 -0.0681047
1]
 [-0.11061386  0.51580216  0.76460638 -0.01872345  0.36535076  0.0570792
1]]

1st 10 elements of our reduced data:

[[  -650.02212207   1585.51909007]
 [  4426.80497937   4042.45150884]
 [  4841.9987068    2578.762176  ]
 [  -990.34643689  -6279.80599663]
 [-10657.99873116  -2159.72581518]
 [  2765.96159271   -959.87072713]
 [   715.55089221  -2013.00226567]
 [  4474.58366697   1429.49697204]
 [  6712.09539718  -2205.90915598]
 [  4823.63435407  13480.55920489]]
```

In [104]:
```
# TODO: Implement your clustering algorithm here, and fit it to the reduced
# The visualizer below assumes your clustering object is named 'clusters'

clusters = KMeans(n_clusters = 3).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 [105]:
```
# 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()])
```

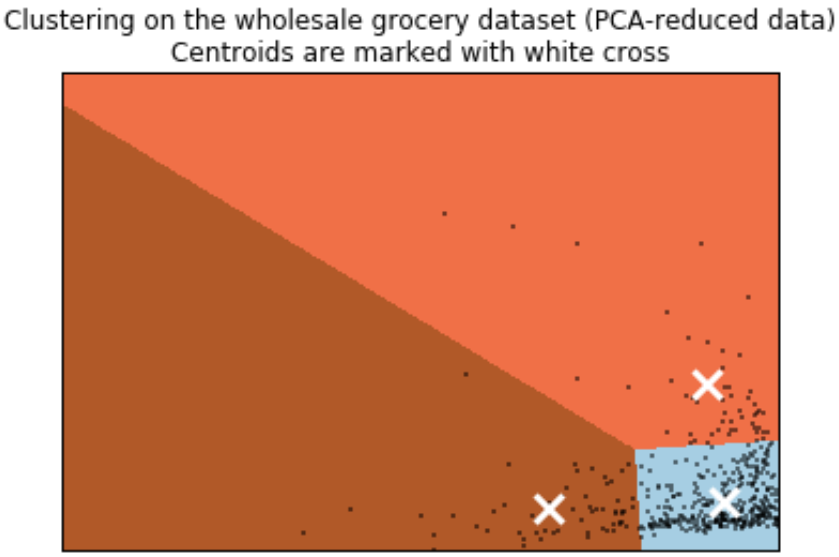
In [106]:
```
# TODO: Find the centroids for KMeans or the cluster means for GMM

centroids = clusters.cluster_centers_
print centroids
```

```
[[  4106.90273941  -3168.41202086]
 [  1497.13461172  24998.27760147]
 [-24220.71188261  -4364.45560022]]
```

In [107]:
```
# 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()
```



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

Answer: Those centroids represent the "average" customer in each cluster (or segment.)

To understand them, we need to first understand the axis of this graph. The X-axis corresponds to the first PCA vector, [-0.97653685 -0.12118407 -0.06154039 -0.15236462 0.00705417 -0.06810471], which, as previously discussed, shows a lack of Fresh foods. The second PCA vector, [-0.11061386 0.51580216 0.76460638 -0.01872345 0.36535076 0.05707921], shows a fair amount of spending in Milk and Groceries.

The X in the brown region, [-24220.71188261 -4364.45560022], represents a customer that spends a lot on Fresh foods but little on Milk and Groceries.

The X in the blue region, [4106.90273941 -3168.41202086], represents a customer that doesn't spend much on Fresh, Milk, or Groceries. Most customers fall in this cluster.

The X in the red region, [1497.13461172 24998.27760147], represents a customer that spends little on Fresh but a lot on Milk and Groceries.

###Conclusions

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

Answer: Personally, I think PCA provided the most insight (and value.) This technique allows you to calculate new basis vectors that best explain the variance in your data. It's been found in this particular data set that just the first 2 PCA vectors accounted for about 86% of the variance in the data. Transforming our 6-dimensional data to these two dimensions not only will make our computations easier from this point on but will also make it practical to visualize it in a plot (something that just can't be done with the original 6-D data.)

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

Answer: Use PCA to reduce the dimensionality down from 6 to 2 and run clustering to separate customers into segments. From this point on, the company should run experiments and perform A/B tests on each customer segment independently instead of testing or making changes across the board. This way, the company will make separate changes to each customer segment which will hopefully minimize the chances of a repeat of its recent mistake of changing to a bulk evening delivery for everyone.

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

Answer: Once we've done A/B testing on each customer segment to best meet each segment's needs, we can rerun clustering every Month or Quarter to see how the customer base is evolving. Some businesses grow while others shrink so it's almost certain that some customers will shift to different segments over time. After taking snapshots of the customer segmentation over time along with the corresponding economic data from the government, it's possible to construct a set of training and test data and fit a regression model for predicting what the customer segmentation will be like in the near future. This will be valuable information for the distributor to prepare for future demand ahead of time.