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 [6]:

```
# 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: Because PCA components give you a higher level of abstraction of attributes, PCA will combine some of the features to create composite features with minimal information loss. A new feature might be the mixture of frozen products and milk products, and that can help infer how much those customers use ice cream products.

On the other hand ICA components give you a lower level of abstraction and try to find some underlying cause of the attributes. When presented with features ICA will look at them as if they're the result of some mixture and try to find the original sources of the data. It will pick out the features that are significant on their own and place less weight on the noise that got mixed into the data. For example if frozen products result in a high positive number where as milk results in a negative number then it could mean that the customer are really buying frozen products and buys milk just because it's convenient.

PCA

In [7]:
```
from sklearn.decomposition import PCA

pca = PCA()
pca.fit(data)
# Print the components and the amount of variance in the data con
tained in each dimension
print 'PCA components:\n{}'.format(pca.components_)
print 'PCA explained variance ratio:\n{}'.format(pca.explained_va
riance_ratio_)
```

```
PCA components:
[[-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]]
PCA explained variance ratio:
[ 0.45961362  0.40517227  0.07003008  0.04402344  0.01502212  0.0
0613848]
```

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 variance drops off quickly after the second dimension. This tells me that I should choose 2 dimensions for my PCA analysis because the first two dimensions collectively account for 86.4% of the total variance.

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

Answer: The dimensions seem to categorize the customer base into 2 types of customers. The first dimension focuses heavily on fresh products and little else, which means they really need fresh produce the most. The second dimension has some grocery, some milk, and some detergents_paper, which means they are much more generalized and they need all kinds of products.

ICA

In [15]:

```
# Note: Adjust the data to have center at the origin first!
from sklearn.decomposition import FastICA
from sklearn import preprocessing

ica = FastICA()
scaled_data = preprocessing.scale(data)
ica.fit(scaled_data)
# Print the independent components
print 'ICA components:\n{}'.format(ica.components_)
print 'ICA components * 1000:\n{}'.format(ica.components_.round
(5) * 100)
```

```
ICA components:
[[ 0.00353186 -0.01744988 -0.11177057  0.00715933  0.13398837  0.
01599162]
 [ 0.00183499  0.07275146 -0.05569191 -0.00176117  0.01569806 -0.
01709741]
 [-0.0109185  -0.00107385  0.00727838  0.05405376 -0.00256072 -0.
01675418]
 [-0.00489855 -0.00152813 -0.00564212 -0.00252916  0.00236046  0.
0509291 ]
 [ 0.00262383 -0.0123842   0.06527092  0.00168117 -0.0094372  -0.
00503297]
 [-0.05025286  0.00632793  0.00699035  0.00324987 -0.01086248  0.
00281258]]
ICA components * 1000:
[[  0.353  -1.745 -11.177   0.716  13.399   1.599]
 [  0.183   7.275  -5.569  -0.176   1.57   -1.71 ]
 [ -1.092  -0.107   0.728   5.405  -0.256  -1.675]
 [ -0.49   -0.153  -0.564  -0.253   0.236   5.093]
 [  0.262  -1.238   6.527   0.168  -0.944  -0.503]
 [ -5.025   0.633   0.699   0.325  -1.086   0.281]]
```

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: The first vector represents customers who are heavy on grocery and detergents_paper, so it could be a general big box store like Walmart.

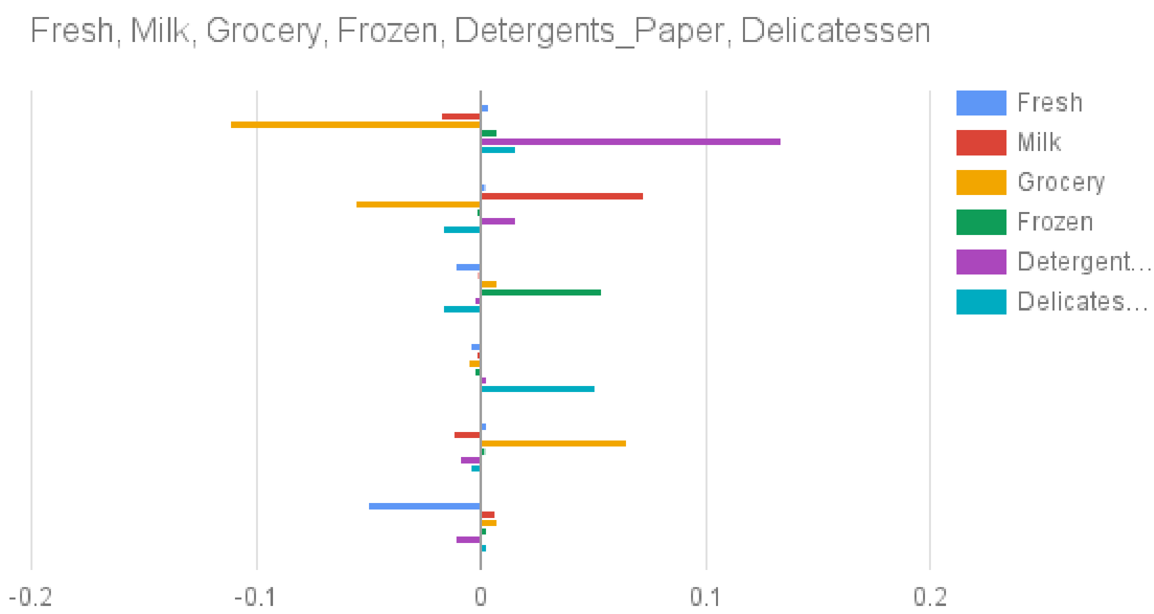
The second one represents customers who are buying milk and grocery, with emphasis on milk, so it could be United Dairy Farmers or some convinent stores.

The third one represents customers who buy a lot of frozen products, so it could be specialty stores like Aldi.

The fourth vector represents customers who are focused on delicatessen, this may be that they have a deli section in the store or that they're a sandwich shop like Subway.

The fifth one is just grocery, so it's most likely general grocery store like Kroger.

The sixth vector represents the customers who buys a lot of fresh products, so it's probably some kind of farmers' market.



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 can help you visualize the data and find the groups with minimal variance. It tries to place centroids that are most equidistant to other points in the same cluster. It performs hard assignment which means all the data points belong to one cluster or another at any iteration. Compared to GMM it's relatively less expensive and faster becuase it doesn't have to calculate probability.

GMM is a parametric probability density model representing a weighted sum of Gaussian densities. It does soft assignment to maximize the probability that the data points belong to one cluster or another. This means GMM can be more expensive and slower but gives more information on the probability of the data clusters.

For this dataset I have chosen GMM approach because it visualizes the plot better. Whereas K means would draw straight edges between the clusters and put the clump on the bottom right into a box, GMM puts them into ellipses along the x axis and y axis which is more intuitive, given that the data on the most bottom right part could be either one of those groups.

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)](http://scikit-learn.org/stable/auto_examples/cluster/plot_kmeans_digits.html) from the sklearn documentation.

In [32]:

```python
# Import clustering modules
from sklearn.cluster import KMeans
from sklearn.mixture import GMM
```

In [33]:

```python
reduced_data = PCA(n_components=2).fit_transform(data)
print reduced_data[:10]  # print upto 10 elements
```

```
[[  -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 [34]:

```
# The visualizer below assumes your clustering object is named 'c
lusters'

# clusters = KMeans(n_clusters=3)
clusters = GMM(n_components=3)
clusters.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_stat
e=None,
  thresh=None, tol=0.001, verbose=0)
```

In [35]:

```
# 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].m
ax() + 1
y_min, y_max = reduced_data[:, 1].min() - 1, reduced_data[:, 1].m
ax() + 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_mi
n, y_max, hy))

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

In [36]:

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

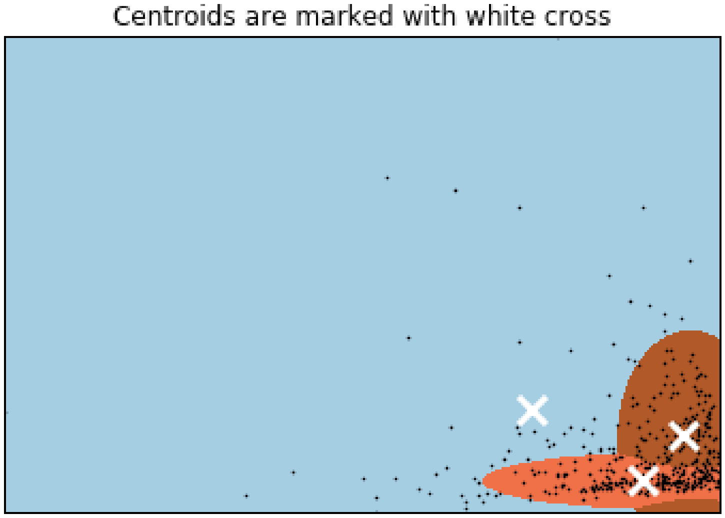
```
[[-17879.18623839  10122.79246625]
 [   269.05318679  -6506.88683442]
 [  6987.95079141   4249.82914044]]
```

In [37]:

```
# 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-reduc
ed 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()
```

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: The central objects in each cluster represent a typical customer in that segment of the market. For example in the dense cluster on the bottom right it would mean that there's many customers that are similar to one another and the central object would be the average, or the plain version of those customers

Conclusions

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

Answer: I feel clustering gives me the most insight into the data because it visualizes the data into definitive groups. This is much faster for me to gain insight into as opposed to trying to extrapolate information from just numbers.

PCA creates composite features, and in this case tells you that the first two composite features accout for most of the variance in the data. This is helpful, especially before clustering we use PCA to reduce dimensionality from 6 to 2, and clustering builds on top of that to make the customer groups even easier to see.

ICA breaks down features and present the original sources, but in this case we don't know how much of the data set is really linearly separable and it doesn't tell us the size of each customer groups.

Clustering is best because it has the most amount of information on seperating the PCA reduced data. With the center of the cluster defined it shows the origin of the axes as between the two centers on the right, and it clearly defined the 3 groups of customers.

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

Answer: I would use clustering to limit the impact of new experiments. For example if the company wants to change something it can apply the change to a certain cluster of customers, and see how the metrics change. This way if the experiments result in negative impact it won't affect the entire customer base.

If the company choose to implement the change, it can limit the implementation on the customer bases that have responded positively to that change, and do more testing on the next group of customers.

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

Answer: From the looks of the PCA reduced data it seems that most of the customer can be placed into somewhere along the x-axis or the y-axis with the origin at the bottom right. Once the company can clarify the traits or labels that apply to those customers then they can provide two different types of customer service that are tailored to those customers, and improve the customer satisfaction rate as a whole.

From the results of these unsupervised learning we can label the clusters, then we can feed these labeled customer data into supervised learning method, such as classify new customers into one of the groups, or estimate the potential demand for new customers.