Machine Learning Engineer Nanodegree

Unsupervised Learning

Project 3: Creating Customer Segments

Welcome to the third project of the Machine Learning Engineer Nanodegree! In this notebook, some template code has already been provided for you, and it will be your job to implement the additional functionality necessary to successfully complete this project. Sections that begin with **'Implementation'** in the header indicate that the following block of code will require additional functionality which you must provide. Instructions will be provided for each section and the specifics of the implementation are marked in the code block with a `'TODO'` statement. Please be sure to read the instructions carefully!

In addition to implementing code, there will be questions that you must answer which relate to the project and your implementation. Each section where you will answer a question is preceded by a **'Question X'** header. Carefully read each question and provide thorough answers in the following text boxes that begin with **'Answer:'**. Your project submission will be evaluated based on your answers to each of the questions and the implementation you provide.

> **Note:** Code and Markdown cells can be executed using the **Shift + Enter** keyboard shortcut. In addition, Markdown cells can be edited by typically double-clicking the cell to enter edit mode.

Getting Started

In this project, you will analyze a dataset containing data on various customers' annual spending amounts (reported in *monetary units*) of diverse product categories for internal structure. One goal of this project is to best describe the variation in the different types of customers that a wholesale distributor interacts with. Doing so would equip the distributor with insight into how to best structure their delivery service to meet the needs of each customer.

The dataset for this project can be found on the UCI Machine Learning Repository (https://archive.ics.uci.edu/ml/datasets/Wholesale+customers). For the purposes of this project, the features `'Channel'` and `'Region'` will be excluded in the analysis — with focus instead on the six product categories recorded for customers.

Run the code block below to load the wholesale customers dataset, along with a few of the necessary Python libraries required for this project. You will know the dataset loaded successfully if the size of the dataset is reported.

In [2]:
```
# Import libraries necessary for this project
import numpy as np
import pandas as pd
import renders as rs
from IPython.display import display # Allows the use of display() for DataFrames

# Show matplotlib plots inline (nicely formatted in the notebook)
%matplotlib inline

# Load the wholesale customers dataset
try:
    data = pd.read_csv("customers.csv")
    data.drop(['Region', 'Channel'], axis = 1, inplace = True)
    print "Wholesale customers dataset has {} samples with {} features each.".forma
t(*data.shape)
except:
    print "Dataset could not be loaded. Is the dataset missing?"
```

```
Wholesale customers dataset has 440 samples with 6 features each.
```

Data Exploration

In this section, you will begin exploring the data through visualizations and code to understand how each feature is related to the others. You will observe a statistical description of the dataset, consider the relevance of each feature, and select a few sample data points from the dataset which you will track through the course of this project.

Run the code block below to observe a statistical description of the dataset. Note that the dataset is composed of six important product categories: **'Fresh'**, **'Milk'**, **'Grocery'**, **'Frozen'**, **'Detergents_Paper'**, and **'Delicatessen'**. Consider what each category represents in terms of products you could purchase.

In [3]:
```
# Display a description of the dataset
display(data.describe())
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
count	440.000000	440.000000	440.000000	440.000000	440.000000	440.000000
mean	12000.297727	5796.265909	7951.277273	3071.931818	2881.493182	1524.870455
std	12647.328865	7380.377175	9503.162829	4854.673333	4767.854448	2820.105937
min	3.000000	55.000000	3.000000	25.000000	3.000000	3.000000
25%	3127.750000	1533.000000	2153.000000	742.250000	256.750000	408.250000
50%	8504.000000	3627.000000	4755.500000	1526.000000	816.500000	965.500000
75%	16933.750000	7190.250000	10655.750000	3554.250000	3922.000000	1820.250000
max	112151.000000	73498.000000	92780.000000	60869.000000	40827.000000	47943.000000

Implementation: Selecting Samples

To get a better understanding of the customers and how their data will transform through the analysis, it would be best to select a few sample data points and explore them in more detail. In the code block below, add **three** indices of your choice to the `indices` list which will represent the customers to track. It is suggested to try different sets of samples until you obtain customers that vary significantly from one another.

In [4]:
```
# TODO: Select three indices of your choice you wish to sample from the dataset
indices = [95, 181, 85]

# Create a DataFrame of the chosen samples
samples = pd.DataFrame(data.loc[indices], columns = data.keys()).reset_index(drop =
 True)
print "Table 0.1: Chosen samples of wholesale customers dataset:"
display(samples)

import seaborn as sns

# Look at percentile ranks
pcts = 100. * data.rank(axis=0, pct=True).iloc[indices].round(decimals=3)
print "\nTable 0.2: Chosen samples percentile ranks"
display(pcts)

# Visualize percentiles with heatmap
print "\nHeat Map"
sns.heatmap(pcts.reset_index(drop=True), annot=True, cmap='YlGnBu');
```

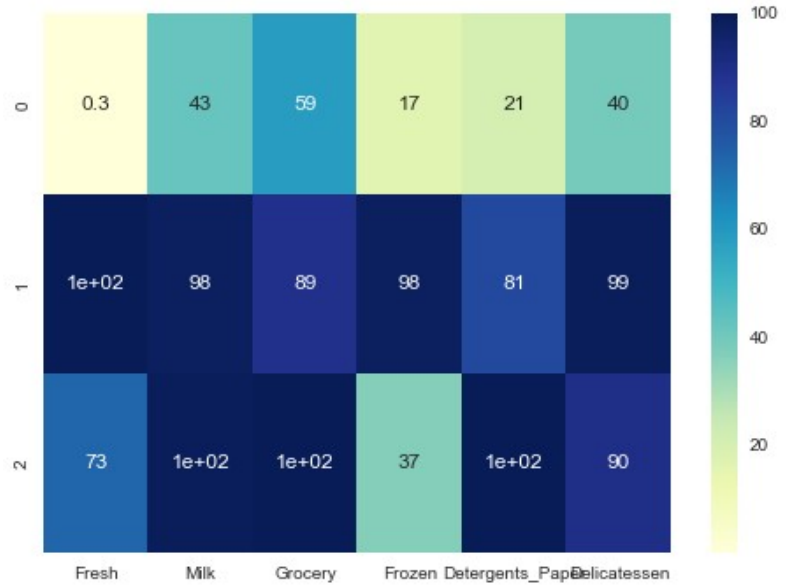
Table 0.1: Chosen samples of wholesale customers dataset:

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	3	2920	6252	440	223	709
1	112151	29627	18148	16745	4948	8550
2	16117	46197	92780	1026	40827	2944

Table 0.2: Chosen samples percentile ranks

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
95	0.3	42.7	58.6	16.6	20.7	39.5
181	100.0	98.4	89.3	98.4	81.1	99.1
85	73.2	99.5	100.0	36.8	100.0	90.0

Heat Map



Note

In order to find samples that are different I picked samples that are at the extreme value of some feature. Customer 95 and 181 are the ones that have min and max Fresh spending, respectively. Cutomer 85 is the one that has maximum Milk. This is confirmed by looking at the ranks (Table 0.2) and the heat map. It turns out that ustomer 85 is also the one that has max Grocery and Detergents_Papaer. In hindsight, although these are reasonable ways to get customers that are different, it also picks extreme data points, which by definition are not particularly representative of the(bulk of the) distribution.

Question 1

Consider the total purchase cost of each product category and the statistical description of the dataset above for your sample customers.
What kind of establishment (customer) could each of the three samples you've chosen represent?
Hint: Examples of establishments include places like markets, cafes, and retailers, among many others. Avoid using names for establishments, such as saying *"McDonalds"* when describing a sample customer as a restaurant.

Answer:

customer 95: Deli/Cafe: low value, possibly a combination of low quantity and low cost, almost no fresh food, moslty milk and groceries. However, the lowest value of fresh (=3) is not met with the lowest value of milk (=55). Thus customer customer 95 is probably selecting this establishment for milk and some groceries.

customer 181: Food market: large quantity of fresh produce. This customer is a big spender, however it is selective. While being the largest spender in fresh products (10x the average) he does not buy proportionately as much milk (6x) or grocery (2x).

customer 85: Supermarket: about same value between grocery and detergents_paper. This is the customer that spent most on detergents (13x the average) but is also the one who spent most on groceries (12x the average)

Implementation: Feature Relevance

One interesting thought to consider is if one (or more) of the six product categories is actually relevant for understanding customer purchasing. That is to say, is it possible to determine whether customers purchasing some amount of one category of products will necessarily purchase some proportional amount of another category of products? We can make this determination quite easily by training a supervised regression learner on a subset of the data with one feature removed, and then score how well that model can predict the removed feature.

In the code block below, you will need to implement the following:

- Assign `new_data` a copy of the data by removing a feature of your choice using the `DataFrame.drop` function.
- Use `sklearn.cross_validation.train_test_split` to split the dataset into training and testing sets.
  - Use the removed feature as your target label. Set a `test_size` of `0.25` and set a `random_state`.
- Import a decision tree regressor, set a `random_state`, and fit the learner to the training data.
- Report the prediction score of the testing set using the regressor's `score` function.

In [5]:
```
# TODO: Make a copy of the DataFrame, using the 'drop' function to drop the given f
eature
from pandas import DataFrame, Series
r2 = []
F = DataFrame(index=data.columns)

for i, col in enumerate(data.columns):
    # print "Considering column '%s' " % col
    y = data[col]
    new_data = data.drop([col], axis=1)

    # TODO: Split the data into training and testing sets using the given feature a
s the target
    from sklearn.cross_validation import train_test_split
    X_train, X_test, y_train, y_test = train_test_split(new_data.values, y, test_si
ze=0.25, random_state=0)

    # TODO: Create a decision tree regressor and fit it to the training set
    from sklearn.tree import DecisionTreeRegressor
    clf = DecisionTreeRegressor(random_state=0)
    clf.fit(X_train, y_train)
    z = pd.Series(clf.feature_importances_, index=new_data.columns, name='Expl. ' +
 col)
    F = pd.concat([F, z], axis=1)

    # TODO: Report the score of the prediction using the testing set
    r2.append(clf.score(X_test, y_test))
    # print "R2 = ", r2[-1]

r2 = pd.Series(r2, index=data.columns)
print "Table 1.1: Predictability of feature given based on all other features, i.e.
 'Fresh' as described by 'Milk', 'Grocery', etc."
display(pd.DataFrame(r2, columns=['R^2']))

corr = data.corr()
for i in range(data.shape[1]):
    for j in range(i,data.shape[1]):
        corr.ix[j, i] = ''
print "\nTable 1.2: Correlation of Features in Original Order"
display(corr)

ix_reord = ['Detergents_Paper', 'Grocery', 'Milk', 'Fresh', 'Frozen', 'Delicatessen
']
corr_reord = data[ix_reord].corr()
for i in range(data.shape[1]):
    for j in range(i,data.shape[1]):
        corr_reord.ix[j, i] = ''
print "\nTable 1.3: Correlation of Features in 'Clustered' Order"
display(corr_reord)


corr = data[ix_reord].corr()
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True
with sns.axes_style("white"):
    ax = sns.heatmap(corr, mask=mask, square=True, annot=True, cmap='RdBu')

# display(F)
```

Table 1.1: Predictability of feature given based on all other features, i.e. 'Fresh' as described by 'Milk', 'Grocery', etc.

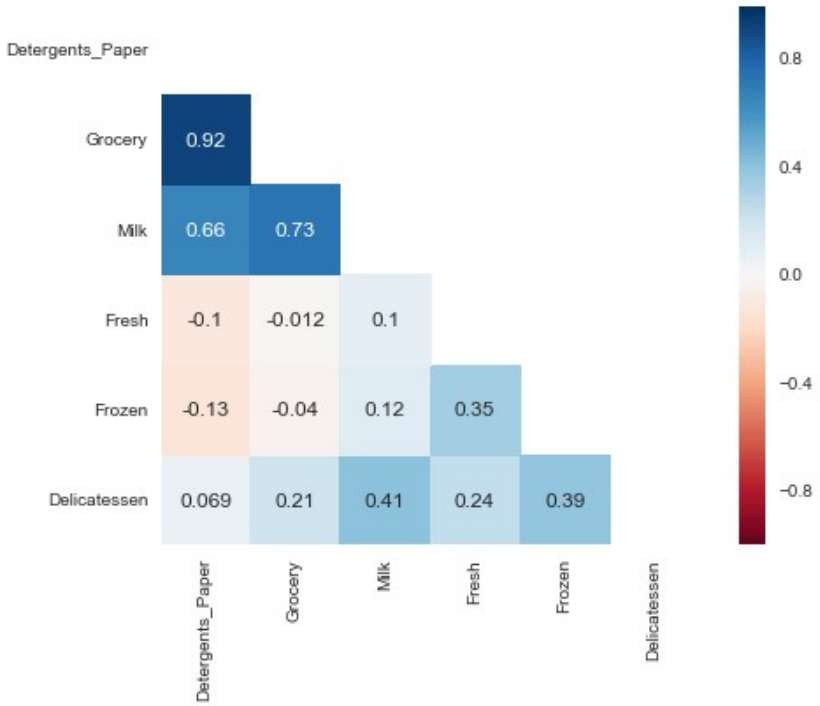
	R^2
Fresh	-0.252470
Milk	0.365725
Grocery	0.602802
Frozen	0.253973
Detergents_Paper	0.728655
Delicatessen	-11.663687

Table 1.2: Correlation of Features in Original Order

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
Fresh		0.10051	-0.0118539	0.345881	-0.101953	0.24469
Milk			0.728335	0.123994	0.661816	0.406368
Grocery				-0.0401927	0.924641	0.205497
Frozen					-0.131525	0.390947
Detergents_Paper						0.0692913
Delicatessen						

Table 1.3: Correlation of Features in 'Clustered' Order

	Detergents_Paper	Grocery	Milk	Fresh	Frozen	Delicatessen
Detergents_Paper		0.924641	0.661816	-0.101953	-0.131525	0.0692913
Grocery			0.728335	-0.0118539	-0.0401927	0.205497
Milk				0.10051	0.123994	0.406368
Fresh					0.345881	0.24469
Frozen						0.390947
Delicatessen						



Question 2

Which feature did you attempt to predict? What was the reported prediction score? Is this feature is necessary for identifying customers' spending habits?
Hint: The coefficient of determination, `R^2`, is scored between 0 and 1, with 1 being a perfect fit. A negative `R^2` implies the model fails to fit the data.

Answer: Looping over all features indicates that the most highly explainable features are: Detergents_Paper ($r^2 = 0.73$) and Grocery ($r^2 = 0.60$), see Table 1.1. Chances are that either of these could be dropped.

A simpler correlation matrix confirms that Detergents_Paper is highly correlated to Grocery and Milk. In addition, Grocery and Milk are also highly correlated among themselves.

This suggests that there is a cluster composed of 3 features: Detergents_Paper, Grocery, and Milk. Then there are 'fringe' features Fresh, Frozen, and Delicatessen which are relatively lowly correlated, among themselves and with the clustered features.

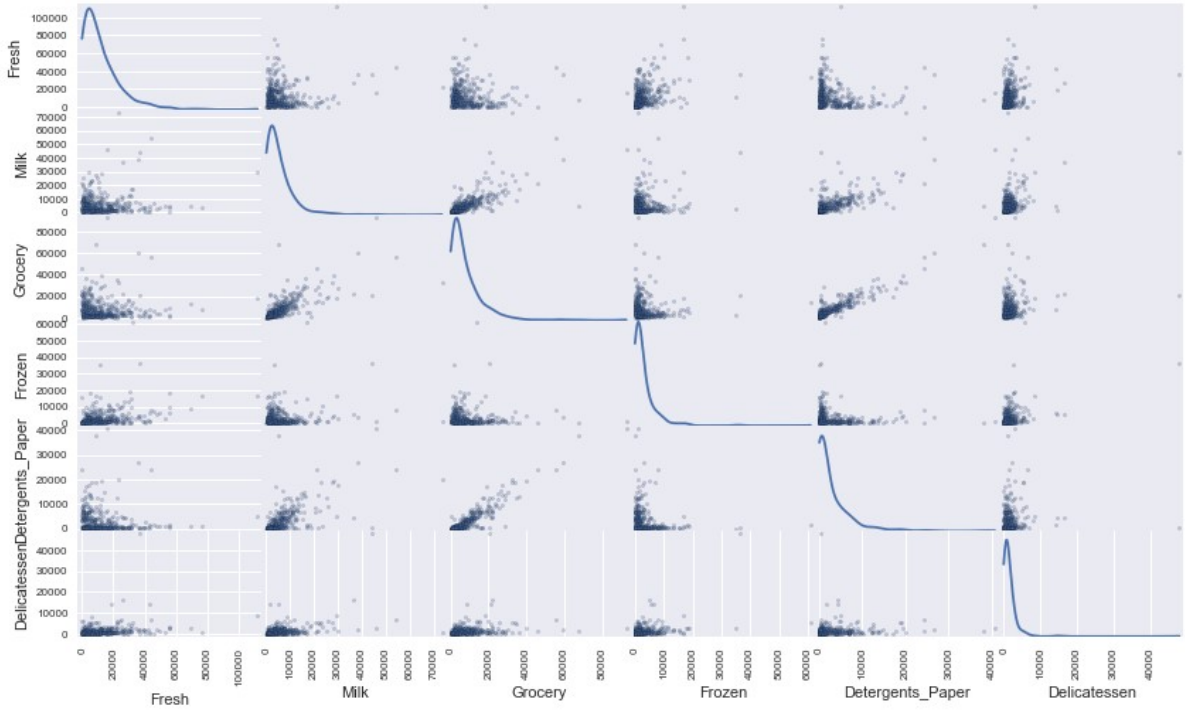
From a narrative point of view, Detergents_Paper, Grocery, and Milk are relatively common items that can be found in many different establishments. Their high correlation could express the fact that those are more 'basic necessities' which are bought often and in generic stores. If this were true, chances are that they would not be particularly descriptive in distinguishing the type of establishment when considered all together. One could siffice. Quite different from say Fresh which would probably indicates a specific store. That said, one of the three features would be necessary to help the algorithm normalize the scale of the purchase, i.e. there are customers who by a lot more than others. One of these three variables would help establish the generic size. Alternatively one could convert the data into z-scores and remove the size effect that way.

To summarize, if I had to reduce the features I would define a 'Bulk' feature = Detergents_Paper + Grocery + Milk, which could be thought of a scaled version of the mean (3x) so that the sum of purchases per csutomer would not change in this transformed data. I would then keep the other features. All in all this would reduce the features from 6 to 4.

Visualize Feature Distributions

To get a better understanding of the dataset, we can construct a scatter matrix of each of the six product features present in the data. If you found that the feature you attempted to predict above is relevant for identifying a specific customer, then the scatter matrix below may not show any correlation between that feature and the others. Conversely, if you believe that feature is not relevant for identifying a specific customer, the scatter matrix might show a correlation between that feature and another feature in the data. Run the code block below to produce a scatter matrix.

In [6]:
```
# Produce a scatter matrix for each pair of features in the data
pd.scatter_matrix(data, alpha = 0.3, figsize = (14,8), diagonal = 'kde');
```



Question 3

Are there any pairs of features which exhibit some degree of correlation? Does this confirm or deny your suspicions about the relevance of the feature you attempted to predict? How is the data for those features distributed?
Hint: Is the data normally distributed? Where do most of the data points lie?

Answer:

The scatter plot reflects the analysis above. The cluster of 3 features: Detergents_Paper, Grocery, and Milk show good correlation, i.e. the mutual scatter plots show points being close to a line.

The distributions are non-Gaussian. This is by necessity since prices are positive. Most prices cluster around low values. A more appropriate distribution would be Log-Normal. If there were no big spenders the distributions would look more Normal, although they would never really be Normal.

Interestingly, the scatter plot shows something that cannot be discerned by simply looking at correlation. Some relationships are L-shaped, e.g. Detergents_Paper and Fresh or Grocery and Fresh. While the correlation is low, there is actually more structure than the correlation suggests. An L-shaped (joint) distribution indicates that customers either buy Detergents_Paper or Fresh (more specifically an XOR choice). Chances are that that tuple (Detergents_Paper, Fresh) is a good distinguishing factor.

Data Preprocessing

In this section, you will preprocess the data to create a better representation of customers by performing a scaling on the data and detecting (and optionally removing) outliers. Preprocessing data is often times a critical step in assuring that results you obtain from your analysis are significant and meaningful.

Implementation: Feature Scaling

If data is not normally distributed, especially if the mean and median vary significantly (indicating a large skew), it is most often appropriate (http://econbrowser.com/archives/2014/02/use-of-logarithms-in-economics) to apply a non-linear scaling — particularly for financial data. One way to achieve this scaling is by using a Box-Cox test (http://scipy.github.io/devdocs/generated/scipy.stats.boxcox.html), which calculates the best power transformation of the data that reduces skewness. A simpler approach which can work in most cases would be applying the natural logarithm.

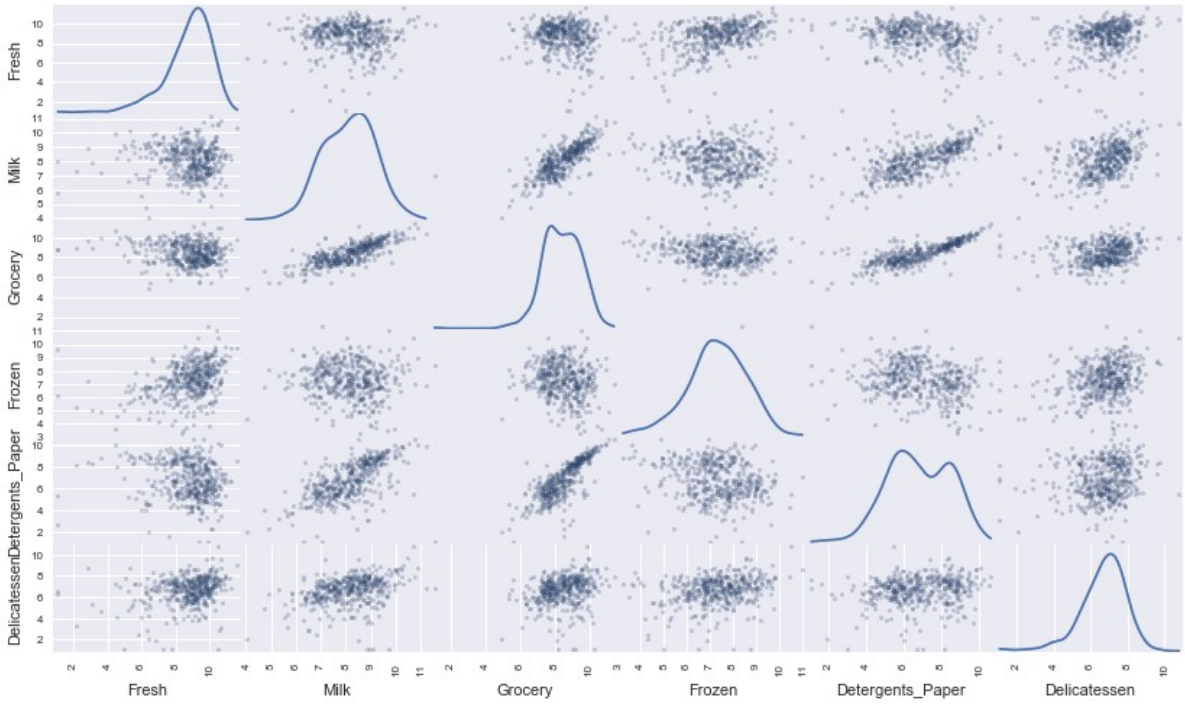
In the code block below, you will need to implement the following:

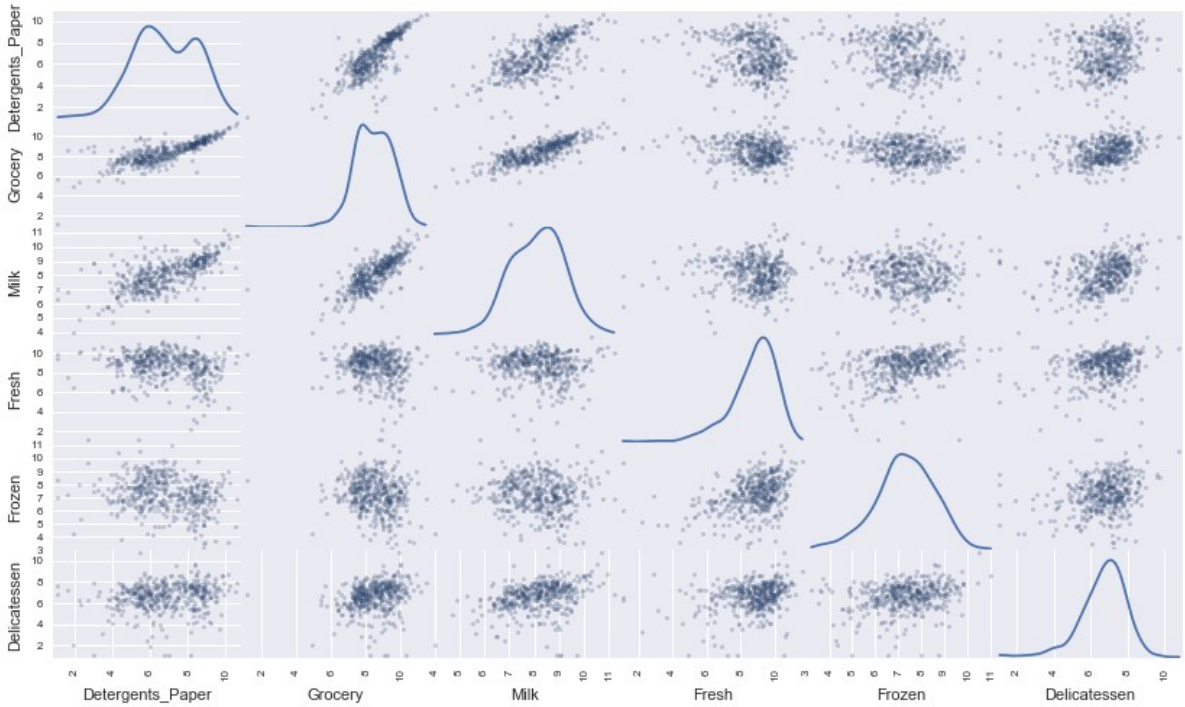
- Assign a copy of the data to `log_data` after applying a logarithm scaling. Use the `np.log` function for this.
- Assign a copy of the sample data to `log_samples` after applying a logrithm scaling. Again, use `np.log`.

In [7]:
```
# TODO: Scale the data using the natural logarithm
log_data = np.log(data.copy())

# TODO: Scale the sample data using the natural logarithm
log_samples = np.log(samples.copy())

# Produce a scatter matrix for each pair of newly-transformed features
pd.scatter_matrix(log_data, alpha = 0.3, figsize = (14,8), diagonal = 'kde');
pd.scatter_matrix(log_data[ix_reord], alpha = 0.3, figsize = (14,8), diagonal = 'kd
e');

corr_reord_log = log_data[ix_reord].corr()
for i in range(log_data.shape[1]):
    for j in range(i,log_data.shape[1]):
        corr_reord_log.ix[j, i] = ''
print "\nCorrelation of Features in 'Clustered' Order (log)"
display(corr_reord_log)
```

```
Correlation of Features in 'Clustered' Order (log)
```

	Detergents_Paper	Grocery	Milk	Fresh	Frozen	Delicatessen
Detergents_Paper		0.796398	0.677942	-0.155871	-0.211576	0.166735
Grocery			0.758851	-0.132713	-0.164524	0.235728
Milk				-0.019834	-0.0553159	0.337833
Fresh					0.383996	0.255186
Frozen						0.254718
Delicatessen						





Observation

After applying a natural logarithm scaling to the data, the distribution of each feature should appear much more normal. For any pairs of features you may have identified earlier as being correlated, observe here whether that correlation is still present (and whether it is now stronger or weaker than before).

Run the code below to see how the sample data has changed after having the natural logarithm applied to it.

In [8]:
```
# Display the log-transformed sample data
display(log_samples)
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	1.098612	7.979339	8.740657	6.086775	5.407172	6.563856
1	11.627601	10.296441	9.806316	9.725855	8.506739	9.053687
2	9.687630	10.740670	11.437986	6.933423	10.617099	7.987524

Extra Note

The correlations of the 3 clustered features (Detergents_Paper, Grocery, and Milk) are maintained. In addition, the correlation of the other features is decreased suggesting that some of it was simply function of the original scaling. Applying logs gets rid of some of that spurious correlation.

Implementation: Outlier Detection

Detecting outliers in the data is extremely important in the data preprocessing step of any analysis. The presence of outliers can often skew results which take into consideration these data points. There are many "rules of thumb" for what constitutes an outlier in a dataset. Here, we will use Tukey's Method for identfying outliers (http://datapigtechnologies.com/blog/index.php/highlighting-outliers-in-your-data-with-the-tukey-method/): An *outlier step* is calculated as 1.5 times the interquartile range (IQR). A data point with a feature that is beyond an outlier step outside of the IQR for that feature is considered abnormal.

In the code block below, you will need to implement the following:

- Assign the value of the 25th percentile for the given feature to `Q1`. Use `np.percentile` for this.
- Assign the value of the 75th percentile for the given feature to `Q3`. Again, use `np.percentile`.
- Assign the calculation of an outlier step for the given feature to `step`.
- Optionally remove data points from the dataset by adding indices to the `outliers` list.

NOTE: If you choose to remove any outliers, ensure that the sample data does not contain any of these points!
Once you have performed this implementation, the dataset will be stored in the variable `good_data`.

In [9]:
```
out_liers = []

# For each feature find the data points with extreme high or low values
for feature in log_data.keys():

    print "Feature '%s'" % feature
    x = log_data[feature]

    # TODO: Calculate Q1 (25th percentile of the data) for the given feature
    Q1 = np.percentile(x, 25)
    print "Q1 = %1.2f" % Q1

    # TODO: Calculate Q3 (75th percentile of the data) for the given feature
    Q3 = np.percentile(x, 75)
    print "Q3 = %1.2f" % Q3

    # TODO: Use the interquartile range to calculate an outlier step (1.5 times the
 interquartile range)
    step = 1.5*(Q3 - Q1)
    print "step = %1.2f" % step

    # Display the outliers
    print "Data points considered outliers for the feature '{}':".format(feature)
    df_outlier = log_data[~((log_data[feature] >= Q1 - step) & (log_data[feature] <
= Q3 + step))]
    #display(df_outlier) # switching this off for better graphical output
    print "Switching this off for better graphical output\n"

    # OPTIONAL: Select the indices for data points you wish to remove
    for i in df_outlier.index:
        out_liers.append(i)

s = Series(out_liers) # convert outliers into a Series object
s_vc = s.value_counts() # use value_counts method to group by same outlier index
valid = [i for i in range(log_data.shape[0]) if not(i in s_vc[s_vc>1])] # keep all
indices that have at most 1 outlier feature

# Remove the outliers, if any were specified
# good_data = log_data.drop(log_data.index[outliers]).reset_index(drop = True)
good_data = log_data.ix[valid,:]

print "Potential outliers = ", len(s_vc)
print "'True' outliers"
print s_vc[s_vc>1]

print "Original data = ", log_data.shape[0]
print "Data without outliers = ", good_data.shape[0]
```

```
Feature 'Fresh'
Q1 = 8.05
Q3 = 9.74
step = 2.53
Data points considered outliers for the feature 'Fresh':
Switching this off for better graphical output

Feature 'Milk'
Q1 = 7.33
Q3 = 8.88
step = 2.32
Data points considered outliers for the feature 'Milk':
Switching this off for better graphical output

Feature 'Grocery'
Q1 = 7.67
Q3 = 9.27
step = 2.40
Data points considered outliers for the feature 'Grocery':
Switching this off for better graphical output

Feature 'Frozen'
Q1 = 6.61
Q3 = 8.18
step = 2.35
Data points considered outliers for the feature 'Frozen':
Switching this off for better graphical output

Feature 'Detergents_Paper'
Q1 = 5.55
Q3 = 8.27
step = 4.09
Data points considered outliers for the feature 'Detergents_Paper':
Switching this off for better graphical output

Feature 'Delicatessen'
Q1 = 6.01
Q3 = 7.51
step = 2.24
Data points considered outliers for the feature 'Delicatessen':
Switching this off for better graphical output

Potential outliers =  42
'True' outliers
154    3
66     2
75     2
128    2
65     2
dtype: int64
Original data =  440
Data without outliers =  435
```

Question 4

Are there any data points considered outliers for more than one feature? Should these data points be removed from the dataset? If any data points were added to the `outliers` *list to be removed, explain why.*

Answer: There are 42 potential outliers (unique customers). Out of those (#154) is an outlier in as many as 3 features. Another four are outliers are outliers in 2 features. The remaining 37 are outliers in only one feature. I suggest we remove only those top 5 outliers (the ones with more than 1 feature being an outlier): 154, 66, 75, 128, and 65.

Feature Transformation

In this section you will use principal component analysis (PCA) to draw conclusions about the underlying structure of the wholesale customer data. Since using PCA on a dataset calculates the dimensions which best maximize variance, we will find which compound combinations of features best describe customers.

Implementation: PCA

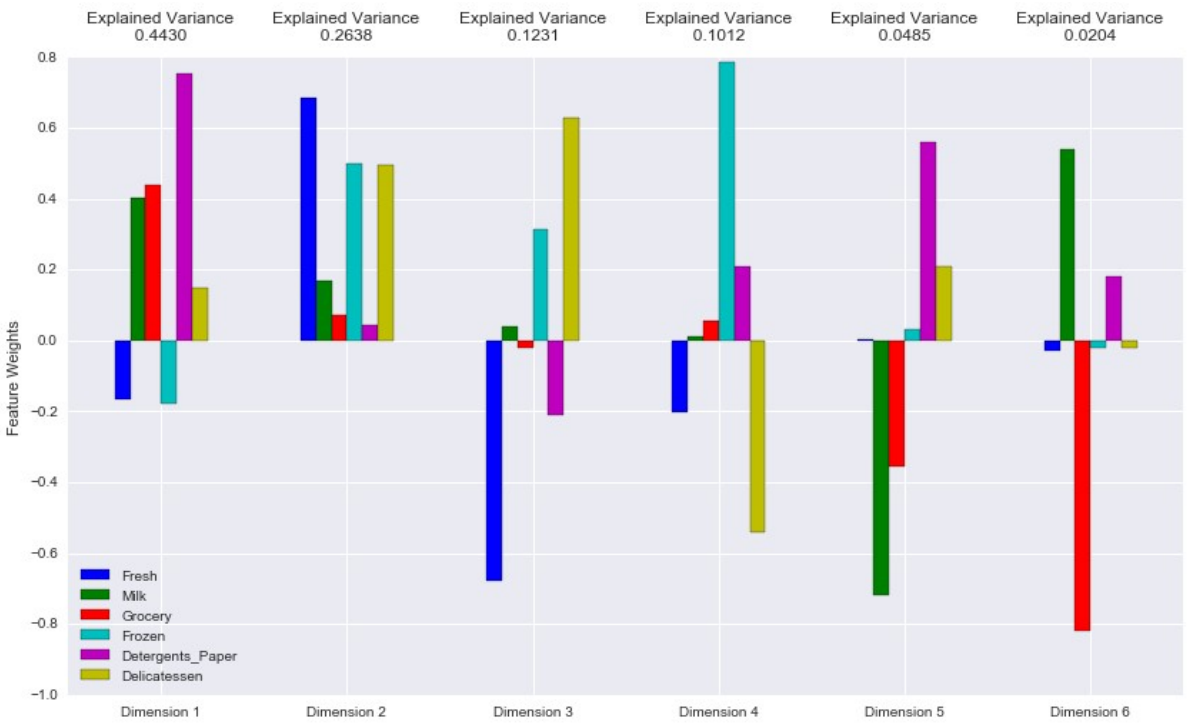
Now that the data has been scaled to a more normal distribution and has had any necessary outliers removed, we can now apply PCA to the `good_data` to discover which dimensions about the data best maximize the variance of features involved. In addition to finding these dimensions, PCA will also report the *explained variance ratio* of each dimension — how much variance within the data is explained by that dimension alone. Note that a component (dimension) from PCA can be considered a new "feature" of the space, however it is a composition of the original features present in the data.

In the code block below, you will need to implement the following:

- Import `sklearn.decomposition.PCA` and assign the results of fitting PCA in six dimensions with `good_data` to `pca`.
- Apply a PCA transformation of the sample log-data `log_samples` using `pca.transform`, and assign the results to `pca_samples`.

In [10]:
```
# TODO: Apply PCA to the good data with the same number of dimensions as features
from sklearn.decomposition import PCA
pca = PCA(n_components=data.shape[1])
pca_all = pca.fit(good_data)

# TODO: Apply a PCA transformation to the sample log-data
pca_samples = pca_all.transform(log_samples)

# Generate PCA results plot
# print type(rs)
pca_results = rs.pca_results(good_data, pca_all)
pca_results

print "Cumulative explained variance\n"
print pca_results['Explained Variance'].cumsum()
print "\n"


## Check that data is de-meaned

#good_data_demean = good_data - good_data.mean()
#pca_results_demean = rs.pca_results(good_data_demean, pca)
#pca_results_demean

# The parameter 'whiten' in PCA will control the rescaling of data by their varianc
e (really n_samples * singular values)
# source: http://scikit-learn.org/stable/modules/generated/sklearn.decomposition.PC
A.html
# In this case the variances are close (see below) so I will keep the pca 'whiten'
to its default value
```

```
Cumulative explained variance

Dimension 1    0.4430
Dimension 2    0.7068
Dimension 3    0.8299
Dimension 4    0.9311
Dimension 5    0.9796
Dimension 6    1.0000
Name: Explained Variance, dtype: float64
```



In [11]:
```
print "Most important factors (by row) explaining a particular feature (by column)"
display(F)

print "\nStandard deviation of log features"
print log_data.std()
```

```
Most important factors (by row) explaining a particular feature (by column)
```

	Expl. Fresh	Expl. Milk	Expl. Grocery	Expl. Frozen	Expl. Detergents_Paper	Expl. Delicatessen
Delicatessen	0.124946	0.132214	0.012718	0.447727	0.022940	NaN
Detergents_Paper	0.090729	0.481405	0.869877	0.162431	NaN	0.069690
Fresh	NaN	0.146786	0.028130	0.205889	0.030676	0.119654
Frozen	0.459906	0.011797	0.024750	NaN	0.015813	0.673129
Grocery	0.145088	0.227798	NaN	0.067078	0.904053	0.061245
Milk	0.179331	NaN	0.064525	0.116875	0.026518	0.076283

```
Standard deviation of log features
Fresh              1.480071
Milk               1.081365
Grocery            1.116172
Frozen             1.284540
Detergents_Paper   1.721020
Delicatessen       1.310832
dtype: float64
```

Question 5

*How much variance in the data is explained **in total** by the first and second principal component? What about the first four principal components? Using the visualization provided above, discuss what the first four dimensions best represent in terms of customer spending.*

Hint: A positive increase in a specific dimension corresponds with an *increase* of the *positive-weighted* features and a *decrease* of the *negative-weighted* features. The rate of increase or decrease is based on the indivdual feature weights.

Answer: The first 2 components combined explain 71% of the variance. The first 4 explain 93%.

- PC1 (Dimension 1):
  - The first dimension is given by mostly Detergents_paper as well as Milk and Grocery, consistent with the 'cluster identified above. It is almost a scaled mean of them (it would be the exact mean if the feature weights for those 3 were exactly equal and all the others were 0
- PC2 (Dimension 2):
  - The second dimension is given by Fresh, Frozen, and Delicatessen, which are the complement of the features determining the first dimension. This would suggest somewhat of another another cluster. I would be careful in calling it a cluster because, as evidenced from correlation analysis, these features and not highly correlated. By this I mean that the 3 features in Dimension 1 can be thought of substitues of one another. For the other 'group' of 3 features it is less clear.
- PC3 (Dimension 3):
  - The third dimension is interesting and reflects somewhat of a choice. Along the positive direction the customer would prefer Delicatessen vs. Fresh. Along the negative direction we'd have the opposite. With a bit of a stretch maybe it reflects health consciousness: either load up on higher-cal foods or go for fresh foods.
- PC4 (Dimension 4):
  - The fourth dimension is similarly reflecting a choice of Frozen vs. Delicatessen. Also note that the variance explained by PC3 and PC4 is almost the same. One can then interpret these two dimensions as being equally important and that they reflect choices, e.g. PC3+PC4 = less Frozen and more Fresh (Delicatessen washes out).

Observation

Run the code below to see how the log-transformed sample data has changed after having a PCA transformation applied to it in six dimensions. Observe the numerical value for the first four dimensions of the sample points. Consider if this is consistent with your initial interpretation of the sample points.

In [12]:
```
# This gives me an error:
# Display sample log-data after having a PCA transformation applied
display(pd.DataFrame(np.round(log_samples, 4)))
display(pd.DataFrame(np.round(pca_samples, 4), columns = pca_results.index.values))
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	1.0986	7.9793	8.7407	6.0868	5.4072	6.5639
1	11.6276	10.2964	9.8063	9.7259	8.5067	9.0537
2	9.6876	10.7407	11.4380	6.9334	10.6171	7.9875

	Dimension 1	Dimension 2	Dimension 3	Dimension 4	Dimension 5	Dimension 6
0	0.5023	-6.0080	5.0055	0.3870	-0.8576	-0.3129
1	2.1899	4.8605	0.0008	0.4827	-0.5041	0.1988
2	5.3316	1.8845	-0.6957	-0.1972	-0.5461	-0.3802

Note:

The first customer is a bit mixed, but the second customer is highly concentrated in dimension 2, whereas the 3rd is highly concentrated in dimension 1. The third customer's representation in the original feature space, i.e. Fresh, Milk, etc., has no partcular pattern standing out. All the values are high, ranging from 6.9 to 11.4. Whereas in the transformed PCA space, it is much clearer that customer 3 'belongs' to the first dimension of the PCA (is explained by PC1).

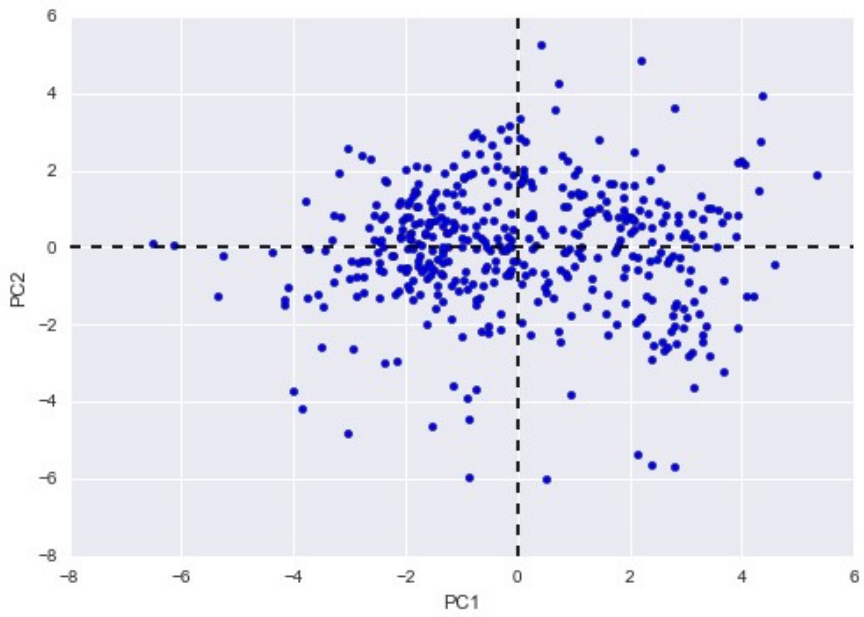
Implementation: Dimensionality Reduction

When using principal component analysis, one of the main goals is to reduce the dimensionality of the data — in effect, reducing the complexity of the problem. Dimensionality reduction comes at a cost: Fewer dimensions used implies less of the total variance in the data is being explained. Because of this, the *cumulative explained variance ratio* is extremely important for knowing how many dimensions are necessary for the problem. Additionally, if a signifiant amount of variance is explained by only two or three dimensions, the reduced data can be visualized afterwards.

In the code block below, you will need to implement the following:

- Assign the results of fitting PCA in two dimensions with `good_data` to `pca`.
- Apply a PCA transformation of `good_data` using `pca.transform`, and assign the reuslts to `reduced_data`.
- Apply a PCA transformation of the sample log-data `log_samples` using `pca.transform`, and assign the results to `pca_samples`.

In [13]:
```
# TODO: Fit PCA to the good data using only two dimensions
pca = PCA(n_components=2)
pca_all2 = pca.fit(good_data)

# TODO: Apply a PCA transformation the good data
reduced_data = pca_all2.transform(good_data)

# TODO: Apply a PCA transformation to the sample log-data
pca_samples  = pca_all2.transform(log_samples)

# Create a DataFrame for the reduced data
reduced_data = pd.DataFrame(reduced_data, columns = ['Dimension 1', 'Dimension 2'])

from matplotlib import pyplot as pl
pl.scatter(reduced_data.ix[:,0], reduced_data.ix[:,1]);
pl.xlabel('PC1');
pl.ylabel('PC2');
pl.axhline(0, color='k', linestyle='--');
pl.axvline(0, color='k', linestyle='--');
```



Observation

Run the code below to see how the log-transformed sample data has changed after having a PCA transformation applied to it using only two dimensions. Observe how the values for the first two dimensions remains unchanged when compared to a PCA transformation in six dimensions.

In [14]:
```
# Display sample log-data after applying PCA transformation in two dimensions
display(pd.DataFrame(np.round(pca_samples, 4), columns = ['Dimension 1', 'Dimension
 2']))
```

	Dimension 1	Dimension 2
0	0.5023	-6.0080
1	2.1899	4.8605
2	5.3316	1.8845

The PCA vectors are actually the same, independent on how many components we use (parameter 'n_components' in PCA). The only difference is that if we try to reconstruct the data using only the first two components we will lose part of the information (about 30% of variance since PC1 and PC2 explain about 70%).

Clustering

In this section, you will choose to use either a K-Means clustering algorithm or a Gaussian Mixture Model clustering algorithm to identify the various customer segments hidden in the data. You will then recover specific data points from the clusters to understand their significance by transforming them back into their original dimension and scale.

Question 6

What are the advantages to using a K-Means clustering algorithm? What are the advantages to using a Gaussian Mixture Model clustering algorithm? Given your observations about the wholesale customer data so far, which of the two algorithms will you use and why?

Answer:

- K-means
  - Pro: scalable (can be used with large sample data), intuitive
  - Con: flat geometry, not too many clusters, assume same variance of the clusters
  - Source: http://scikit-learn.org/stable/modules/clustering.html (http://scikit-learn.org/stable/modules/clustering.html)
- Gaussian Mixture Model
  - Pro: speed and doesn't bias cluster size, clusters can have different variances, probabilistic classification
  - Con: covariance matrix might be difficult to determine if there is not sufficient data; it will use all components; clusters have a specific shape (ellipsoids). I assume it will not be great for non-convex clusters; assumes data is Gaussian
  - Source: http://scikit-learn.org/stable/modules/mixture.html (http://scikit-learn.org/stable/modules/mixture.html)

Given that the data set is small (thus no speed/size issues) and so is the numbers of clusters, I would not see a particular drawback in using either. In addition, since the marginal variances of log data are comparable k-means should be fine. I would slightly prefer k-means, mostly because I need to pick one and it might be slightly more intuitive.

Implementation: Creating Clusters

Depending on the problem, the number of clusters that you expect to be in the data may already be known. When the number of clusters is not known *a priori*, there is no guarantee that a given number of clusters best segments the data, since it is unclear what structure exists in the data — if any. However, we can quantify the "goodness" of a clustering by calculating each data point's *silhouette coefficient*. The silhouette coefficient (http://scikit-learn.org/stable/modules/generated/sklearn.metrics.silhouette_score.html) for a data point measures how similar it is to its assigned cluster from -1 (dissimilar) to 1 (similar). Calculating the *mean* silhouette coefficient provides for a simple scoring method of a given clustering.

In the code block below, you will need to implement the following:

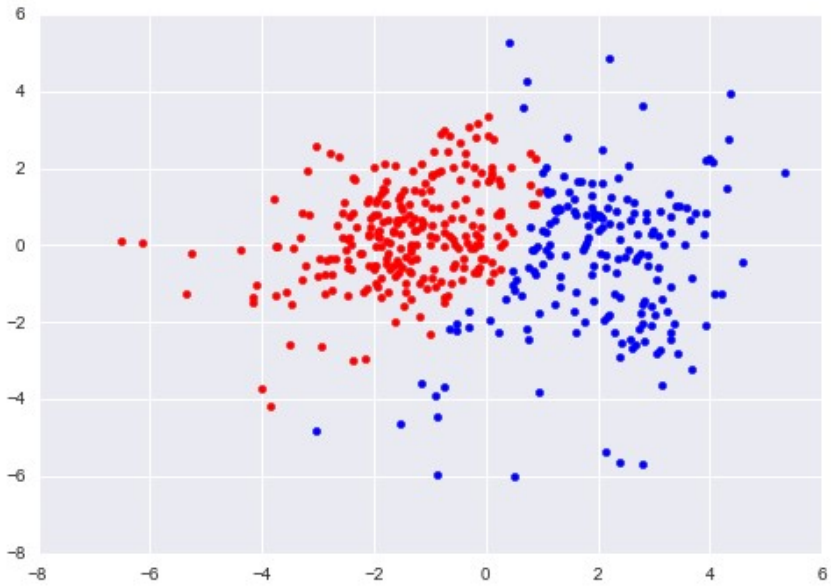
- Fit a clustering algorithm to the `reduced_data` and assign it to `clusterer`.
- Predict the cluster for each data point in `reduced_data` using `clusterer.predict` and assign them to `preds`.
- Find the cluster centers using the algorithm's respective attribute and assign them to `centers`.
- Predict the cluster for each sample data point in `pca_samples` and assign them `sample_preds`.
- Import sklearn.metrics.silhouette_score and calculate the silhouette score of `reduced_data` against `preds`.
  - Assign the silhouette score to `score` and print the result.

In [15]:
```
# K-Means

# TODO: Apply your clustering algorithm of choice to the reduced data
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

n_clusters = [2, 3, 4, 5, 6]
nC = len(n_clusters)
score = np.zeros((nC, 1))
clr = ['r', 'b', 'y', 'm', 'c', 'k']

for i, n_cl in enumerate(n_clusters):
    print "Fitting with # clusters = %i" % n_cl
    clf = KMeans(init='k-means++', n_clusters=n_cl, n_jobs=-1)
    clf.fit(reduced_data)

    # TODO: Predict the cluster for each data point
    preds = clf.predict(reduced_data)

    # TODO: Find the cluster centers
    centers = clf.cluster_centers_

    # TODO: Predict the cluster for each transformed sample data point
    sample_preds = clf.predict(pca_samples)

    for j in range(n_cl):
        ix = preds==j
        pl.scatter(reduced_data.ix[ix,0], reduced_data.ix[ix,1], color=clr[j])

    # TODO: Calculate the mean silhouette coefficient for the number of clusters ch
osen
    score[i] = silhouette_score(reduced_data, clf.labels_)
    print "Score (# clusters = %i) = %1.2f" % (n_cl, score[i])
```

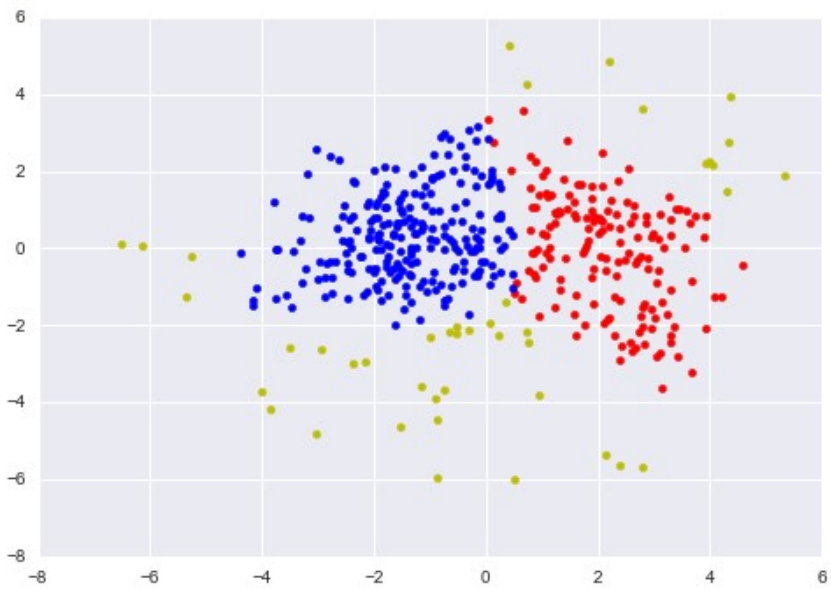
```
Fitting with # clusters = 2
Score (# clusters = 2) = 0.43
Fitting with # clusters = 3
Score (# clusters = 3) = 0.40
Fitting with # clusters = 4
Score (# clusters = 4) = 0.33
Fitting with # clusters = 5
Score (# clusters = 5) = 0.35
Fitting with # clusters = 6
Score (# clusters = 6) = 0.36
```

In [17]:
```
# GMM

from sklearn import mixture
clfGMM = mixture.GMM(n_components=2,covariance_type='full')
aicGMM = np.zeros_like(score)
bicGMM = np.zeros_like(score)
scoreGMM = np.zeros_like(score)
for i, n_cl in enumerate(n_clusters):
    print "Fitting with # clusters = %i" % n_cl
    clfGMM = mixture.GMM(n_components=n_cl, covariance_type='full')
    clfGMM.fit(reduced_data)

    # TODO: Predict the cluster for each data point
    preds = clfGMM.predict(reduced_data)

    # TODO: Find the cluster centers
    centers = clfGMM.means_
    covars  = clfGMM.covars_

    # TODO: Predict the cluster for each transformed sample data point
    sample_preds = clfGMM.predict(pca_samples)

    for j in range(n_cl):
        ix = preds==j
        pl.scatter(reduced_data.ix[ix,0], reduced_data.ix[ix,1], color=clr[j])
    pl.show()

    # TODO: Calculate the mean silhouette coefficient for the number of clusters ch
osen
    # Find out how you get the classification, is it via prob_a?
    scoreGMM[i] = silhouette_score(reduced_data, preds)
    print "Score (# clusters = %i) = %1.2f" % (n_cl, scoreGMM[i])
    aicGMM[i] = clfGMM.aic(reduced_data)
    bicGMM[i] = clfGMM.bic(reduced_data)
    print "AIC score (# clusters = %i) = %1.2f" % (n_cl, aicGMM[i])
    print "BIC score (# clusters = %i) = %1.2f" % (n_cl, bicGMM[i])

df_scoreGMM = DataFrame({'aicGMM': aicGMM[:,0], 'bicGMM': bicGMM[:,0]}, index=n_clu
sters)

# You want minimum AIC or BIC


# Choose optimal

n_cl_optGMM = 2
clfGMM = mixture.GMM(n_components=n_cl_optGMM, covariance_type='full')
clfGMM.fit(reduced_data)
preds = clfGMM.predict(reduced_data)
centers = clfGMM.means_
covars  = clfGMM.covars_


# Display data

# Scatter
from matplotlib.patches import Ellipse
ax = pl.subplot(111, aspect='equal')
for j in range(n_cl_optGMM):
    ix = preds==j
    ax.scatter(reduced_data.ix[ix,0], reduced_data.ix[ix,1], color=clr[j])
    lam2, v = np.linalg.eig(covars[:,:,j])
    lam = np.sqrt(lam2)
    for k in [1, 2, 4, 6]:
```

```
Fitting with # clusters = 2
```

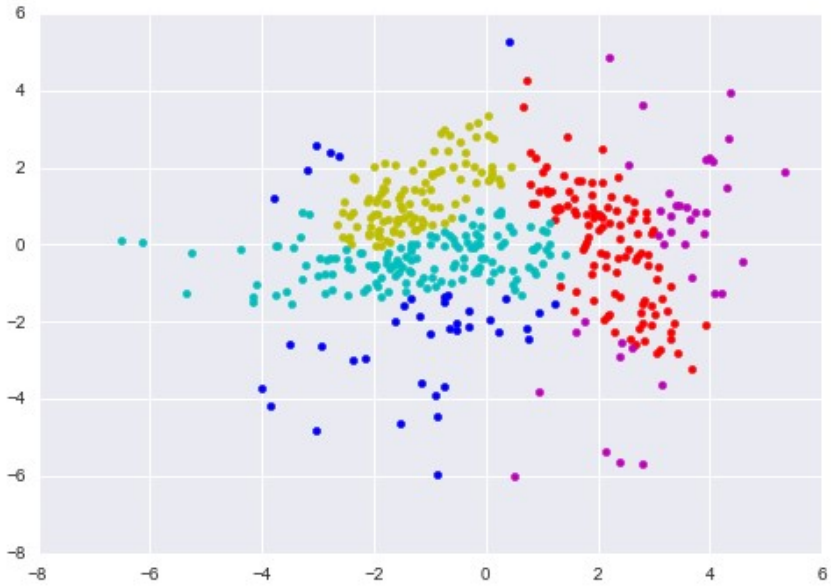


```
Score (# clusters = 2) = 0.41
AIC score (# clusters = 2) = 3525.50
BIC score (# clusters = 2) = 3570.33
Fitting with # clusters = 3
```

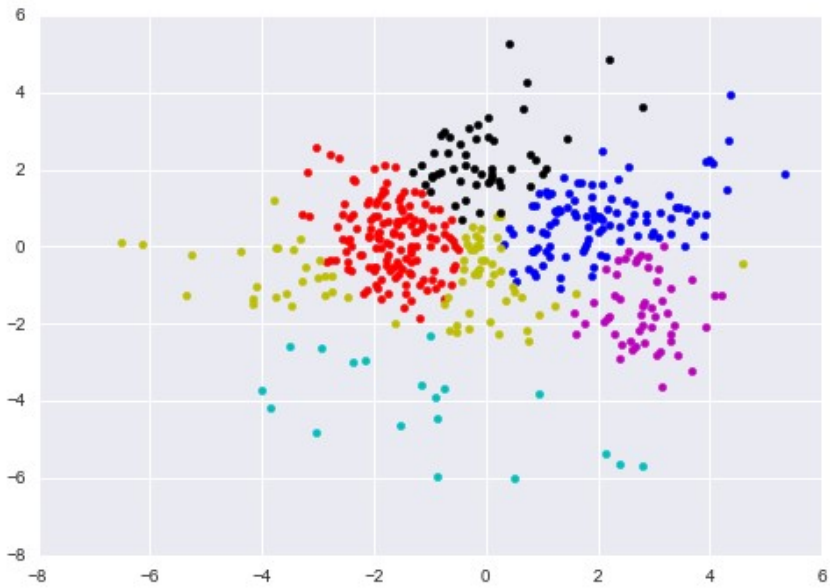


```
Score (# clusters = 3) = 0.40
AIC score (# clusters = 3) = 3503.64
BIC score (# clusters = 3) = 3572.92
Fitting with # clusters = 4
```


```
Score (# clusters = 4) = 0.29
AIC score (# clusters = 4) = 3509.67
BIC score (# clusters = 4) = 3603.40
Fitting with # clusters = 5
```



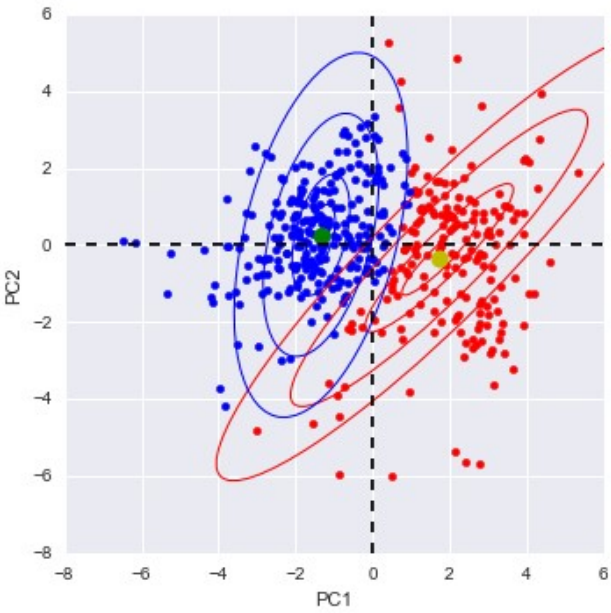

```
Score (# clusters = 5) = 0.19
AIC score (# clusters = 5) = 3493.47
BIC score (# clusters = 5) = 3611.66
Fitting with # clusters = 6
```

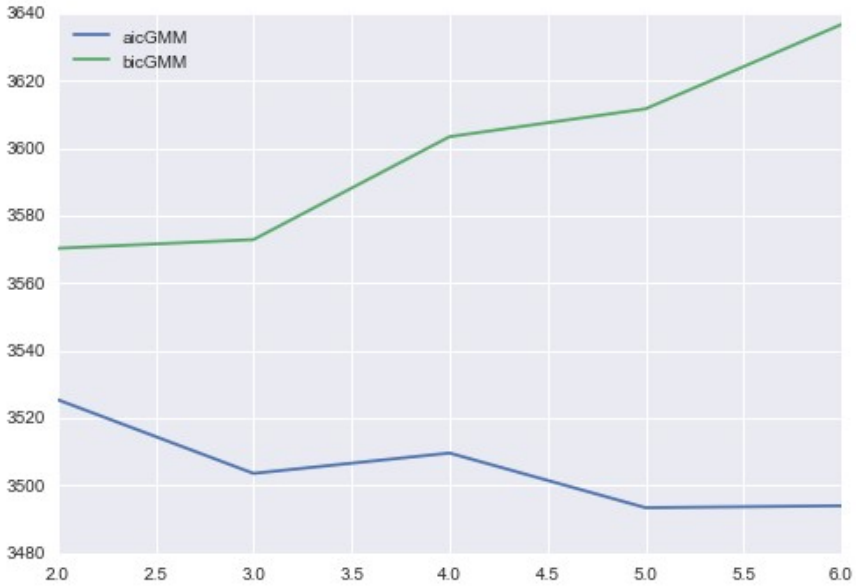


```
Score (# clusters = 6) = 0.28
AIC score (# clusters = 6) = 3494.03
BIC score (# clusters = 6) = 3636.67
```

	aicGMM	bicGMM
2	3525.499412	3570.328219
3	3503.635485	3572.916367
4	3509.669798	3603.402757
5	3493.473533	3611.658568
6	3494.034966	3636.672077

```
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0xccf7240>
```





Question 7

Report the silhouette score for several cluster numbers you tried. Of these, which number of clusters has the best silhouette score?

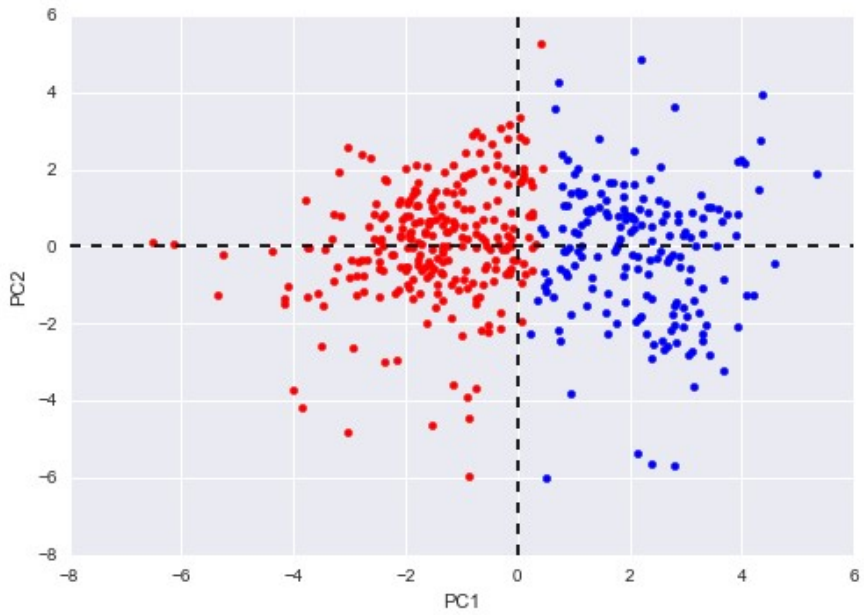
Answer:

The best silhouette score is 0.43 with 2 clusters.

After feedback from the last review I added an analysis with GMM. Using AIC and BIC criterion would yield different choices of optimal number of clusters. However, according to the silhouette measure for GMM we would also infer that 2 clusters is the best choice.

In [18]:
```
n_cl = 2

print "Fitting with # clusters = %i" % n_cl
clf = KMeans(init='k-means++', n_clusters=n_cl, n_jobs=-1)
clf.fit(reduced_data)

# TODO: Predict the cluster for each data point
preds = clf.predict(reduced_data)

# TODO: Find the cluster centers
centers = clf.cluster_centers_

# TODO: Predict the cluster for each transformed sample data point
sample_preds = clf.predict(pca_samples)

for j in range(n_cl):
    ix = preds==j
    pl.scatter(reduced_data.ix[ix,0], reduced_data.ix[ix,1], color=clr[j])
pl.xlabel('PC1');
pl.ylabel('PC2');
pl.axhline(0, color='k', linestyle='--');
pl.axvline(0, color='k', linestyle='--');


# TODO: Calculate the mean silhouette coefficient for the number of clusters chosen
score_opt = silhouette_score(reduced_data, clf.labels_)
print "Score (# clusters = %i) = %1.2f" % (n_cl, score_opt)
```

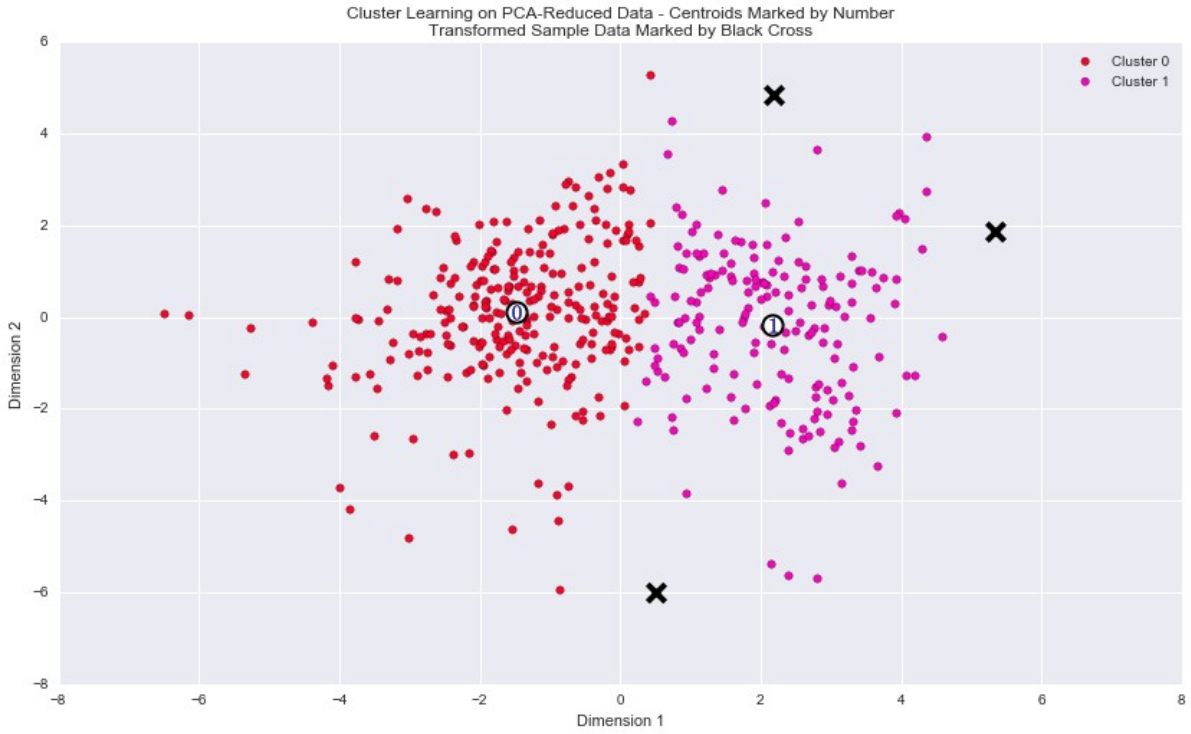
```
Fitting with # clusters = 2
Score (# clusters = 2) = 0.43
```



Cluster Visualization

Once you've chosen the optimal number of clusters for your clustering algorithm using the scoring metric above, you can now visualize the results by executing the code block below. Note that, for experimentation purposes, you are welcome to adjust the number of clusters for your clustering algorithm to see various visualizations. The final visualization provided should, however, correspond with the optimal number of clusters.

In [19]:
```
# Display the results of the clustering from implementation
rs.cluster_results(reduced_data, preds, centers, pca_samples)
```



Implementation: Data Recovery

Each cluster present in the visualization above has a central point. These centers (or means) are not specifically data points from the data, but rather the *averages* of all the data points predicted in the respective clusters. For the problem of creating customer segments, a cluster's center point corresponds to *the average customer of that segment*. Since the data is currently reduced in dimension and scaled by a logarithm, we can recover the representative customer spending from these data points by applying the inverse transformations.

In the code block below, you will need to implement the following:

- Apply the inverse transform to `centers` using `pca.inverse_transform` and assign the new centers to `log_centers`.
- Apply the inverse function of `np.log` to `log_centers` using `np.exp` and assign the true centers to `true_centers`.

In [20]:
```
# TODO: Inverse transform the centers
log_centers = pca_all2.inverse_transform(centers)

# TODO: Exponentiate the centers
true_centers = np.exp(log_centers)

# Display the true centers
segments = ['Segment {}'.format(i) for i in range(0,len(centers))]
true_centers = pd.DataFrame(np.round(true_centers), columns = data.keys())
true_centers.index = segments
display(true_centers)
means = np.round(data.mean())
med = np.round(data.median())
print "\nMean"
display(means)
print "\nMedian"
display(med)
print "\nTotal spending:"
display(np.round(true_centers.sum(axis=1)))

print "\nSpending compared to median"
display(true_centers - med)

print "\nSpending compared to mean"
display(true_centers - means)
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
Segment 0	8867	1897	2477	2088	294	681
Segment 1	4005	7900	12104	952	4561	1036

```
Mean

Fresh               12000
Milk                 5796
Grocery              7951
Frozen               3072
Detergents_Paper     2881
Delicatessen         1525
dtype: float64

Median

Fresh               8504
Milk                3627
Grocery             4756
Frozen              1526
Detergents_Paper     816
Delicatessen         966
dtype: float64

Total spending:

Segment 0    16304
Segment 1    30558
dtype: float64

Spending compared to median
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
Segment 0	363	-1730	-2279	562	-522	-285
Segment 1	-4499	4273	7348	-574	3745	70

```
Spending compared to mean
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
Segment 0	-3133	-3899	-5474	-984	-2587	-844
Segment 1	-7995	2104	4153	-2120	1680	-489

Question 8

Consider the total purchase cost of each product category for the representative data points above, and reference the statistical description of the dataset at the beginning of this project. *What set of establishments could each of the customer segments represent?*
Hint: A customer who is assigned to `'Cluster X'` should best identify with the establishments represented by the feature set of `'Segment X'`.

Answer:

Segment 0 is described by a customer that buys more stuff (about twice as much than Segment 1) but mostly in everything but Fresh and Frozen that are purchased in much less quantity than the average (or median). On the contrary the customer buys a lot more Detergents_paper than the average. Segment 0 could be reflective of a generic (non-food) related store. It could be something like a pharmacy or a convenience store.

Segment 1 on the other hand could be a dedicated food store. It buys a more Fresh and Frozen than the median. As a side, note that he also buys less than the mean in any category. I picked the median to remove the strong skew.

Question 9

*For each sample point, which customer segment from **Question 8** best represents it? Are the predictions for each sample point consistent with this?*

Run the code block below to find which cluster each sample point is predicted to be.

In [21]:
```
# Display the predictions
for i, pred in enumerate(sample_preds):
    print "Sample point", i, "predicted to be in Cluster", pred
```

```
Sample point 0 predicted to be in Cluster 1
Sample point 1 predicted to be in Cluster 1
Sample point 2 predicted to be in Cluster 1
```

Answer:

I would start with the third customer because it is the most clear-cut. The classification makes sense since he loaded up on Grocery and Detergents_paper. This is also consistent with the PCA projection (it's the cross to the most right side of the chart).

The first customer is a low spender but comparatively very concentrated on Milk and Grocery, so it does make sense that he would be classified as 0, although the high Frozen compared to Detergents_paper casts some doubts.

The second customer is the hardest. He has high Fresh (10x the mean) and Frozen (5x the mean) but also high Grocery (2x) and high Milk (4x) and Detergents_paper (2x). All-in-all it would seem more a egment 1 type of customer.

Conclusion

Question 10

Companies often run A/B tests (https://en.wikipedia.org/wiki/A/B_testing) when making small changes to their products or services. If the wholesale distributor wanted to change its delivery service from 5 days a week to 3 days a week, how would you use the structure of the data to help them decide on a group of customers to test?
Hint: Would such a change in the delivery service affect all customers equally? How could the distributor identify who it affects the most?

Answer:

Since Segment 0 spends a lot more than Segment 1, I would focus on Segment 1. Targeting specific stores (food-related stores) would select the smaller subset of customers with reduced impact. The A/B test would be to:

- Run the 5 days service on all customers for 1 week ('A') then
- Run the 3 day service only for Segment 1 customers and 5 day service for Segment 0 ('B')
- Use results on Segment 0 for test A and B, both of which had a 5 day service to normalize results
- Compare results of Segment 1 on a thus-normalized basis

This explanation is a bit vague on the selection of Segment 0 vs. Segment 1 customers, as if one could know. In reality (and fortunately) since this is a delivery service the provider should know which store they are delivering from. According to the previous analysis, we would simply need to classify the store into 0 (non-food specific) or 1 (food specific).

Alternatively, one could use only Segment 1 customers by running 5 day delivery and 3 day delivery on alternative weeks.

Question 11

Assume the wholesale distributor wanted to predict a new feature for each customer based on the purchasing information available. How could the wholesale distributor use the structure of the data to assist a supervised learning analysis?
Hint: What other input feature could the supervised learner use besides the six product features to help make a prediction?

Answer:

I am still not 100% sure I understand the question. Please see below for previous trials.

One could use the PCA features as new inputs into a supervised learner.

Previous Answer:

The question asks for a new feature in general. I am not sure the following answers the question, but here is my interpretation.

Any piece of information that helps identifying the type of store would help. The analysis above suggests that customers' spending habits fall into 2 categories. These categories could essentially split the universe of stores into two classes (this is maybe likely, but not necessary: one can think of a world were therea are only 'giga'-stores that provide any product but customers could still purchase different things from different stores, e.g. for quality reasons). We know or we are suggesting that there are two such classes but we don't know which one they are. If we could gather more information on the store it would help us solidify the analysis. This is also quite important in practice since when a new customer comes we wouldn't know how to classify him in advance, which is necessary if we want to be selective on the delivery service option we want to offer (5 day or 3 day). However, we would be able to make that distinction if we knew where he needs the delivery from. Otherwise we could only distinguish if we knew his spending habit.

Also (and maybe this was the question), suppose we had a supervised problem where the features are the 6 above and the target were the type of store (only one of two types). One could first run an unsupervised learning algo on the features (as we did so far) and potentially come up with clusters. To the degree to which those clusters coincide with the targets it will inform the data scientist on the likelyhood of success of the supervised algo. Suppose for example that we we obtained two neatly separated clusters, let's say a ball of points on the right and a ball on the left. Suppose the targets were not such that the ball on the left was one class and the one on the right the other, but instead the targets would split each ball into two hemispheres so that the upper hemisphere of each ball corresponded to one class and the lower to the other. In that case the supervised learning algorithm would have a much harder time, because it means that it will need to be able to distinguish two points that are quite similar in the original space but belong to different classes in the target space (these would be the points close to the equator in the two balls).

If we were to predict churning, we might want to measure the degree of tolerance for less frequent delivery. Depending on the product type if there were information on delivery options (overnight, 2-day shipping, and standard shipping) that might tells us something. For example, customers who use overnight shipping would proabably churn with a 3-day delivery system.

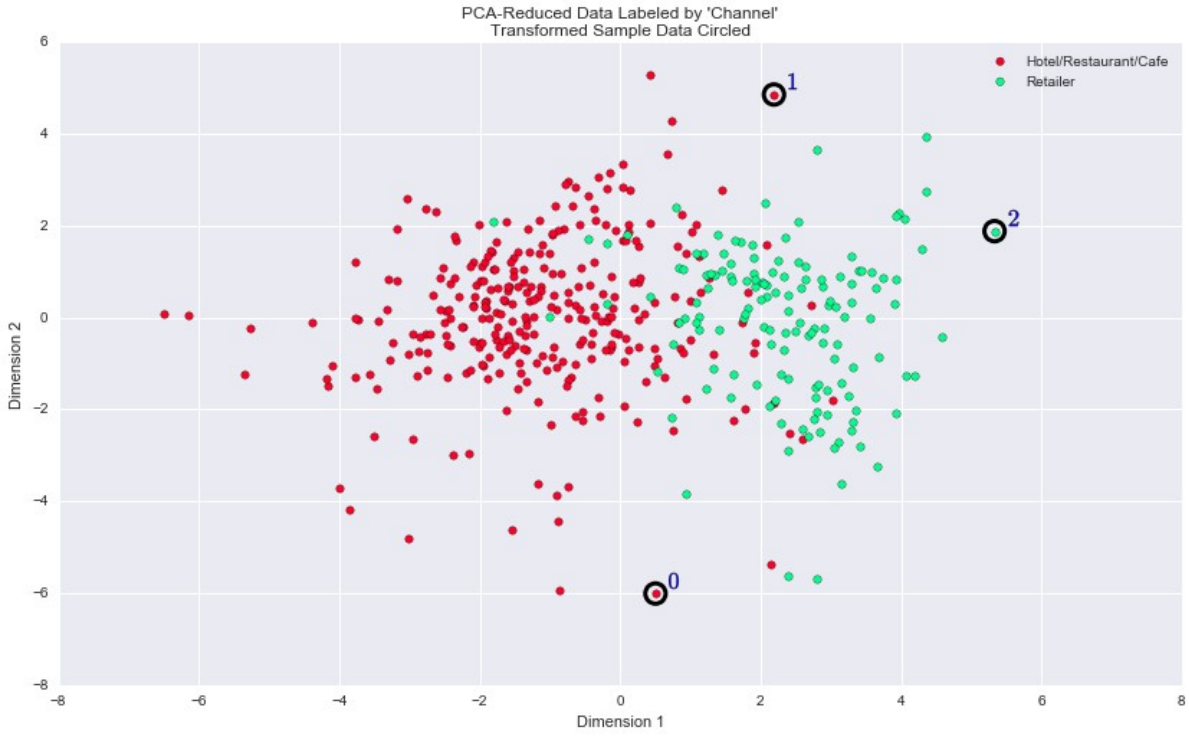
Another measure could be the frequency of delivery, for repeated customers. A customer that receives more deleveries of lower volume might be more invclined to churn than a customer buying less frequently and in bulk.

Visualizing Underlying Distributions

At the beginning of this project, it was discussed that the `'Channel'` and `'Region'` features would be excluded from the dataset so that the customer product categories were emphasized in the analysis. By reintroducing the `'Channel'` feature to the dataset, an interesting structure emerges when considering the same PCA dimensionality reduction applied earlier on to the original dataset.

Run the code block below to see how each data point is labeled either `'HoReCa'` (Hotel/Restaurant/Cafe) or `'Retail'` the reduced space. In addition, you will find the sample points are circled in the plot, which will identify their labeling.

In [19]:
```
# Display the clustering results based on 'Channel' data
outliers = [154, 66, 75, 128, 65] # from analysis above
rs.channel_results(reduced_data, outliers, pca_samples)
#rs.channel_results(reduced_data, list(out_liers), pca_samples)
```



Question 12

How well does the clustering algorithm and number of clusters you've chosen compare to this underlying distribution of Hotel/Restaurant/Cafe customers to Retailer customers? Are there customer segments that would be classified as purely 'Retailers' or 'Hotels/Restaurants/Cafes' by this distribution? Would you consider these classifications as consistent with your previous definition of the customer segments?

Answer:

The clustering algorithm did a good job in finding the clusters and a total of 2 clsuters seems an appropriate choice. The correspondence between the suggested clusters and the Channel is 1-to-1: Retailers is Segment 0 and Hotels/Restaurant/Cafe is Segment 1. The clusters do not purely coincide with the Channel label because of mixture of points closer to the boundary. Certainly the third customer is classified consistently. The other two are quite close to the (fuzzy) boundary and I am not very surprised that they belog to a different label.

As a final note, this fits well with the discussion of clusters in the (unsupervised) features and supervised classification. As evidenced by the figure in this example they correspond quite well.

Note: Once you have completed all of the code implementations and successfully answered each question above, you may finalize your work by exporting the iPython Notebook as an HTML document. You can do this by using the menu above and navigating to
File -> Download as -> HTML (.html). Include the finished document along with this notebook as your submission.