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 [30]:
```
# 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 D

# 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
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 [31]:
```
# Display a description of the dataset
display(data.describe())
```

	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

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
indices = [44,100,232]

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

```
Chosen samples of wholesale customers dataset:
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	9670	7027	10471	541	4618	65
1	11594	7779	12144	3252	8035	3029
2	25962	1780	3838	638	284	834

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:

44

- Establishment 44 could be a house cleaning company. Having most of their purchases below the mean besides the Grocery and milk slightly above the average and the detergents paper way peaked compared to the rest. It can be the customer's occupation to use detergent papers on a day to day basis. This narrows down to a small house cleaning company.

100

- Establishment 100 could be super market. Having all the purchaes above the mean, and the detergent_paper spiked above the 75% percentile. It must be a day to day visit for people to go to purchase a detergent paper on the way home.

232

- Having a high purchase of fresh food indicate the 232 establish could be a salad serving restaurant. The establishment provide little 25% percentile of the frozen food indicates the customer may cook their own food.

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 [13]:
```
# TODO: Make a copy of the DataFrame, using the 'drop' function to drop
from sklearn.cross_validation import train_test_split
# Make new dataframe. Calling it new_data

new_data = pd.read_csv("customers.csv")
new_data.drop(['Region', 'Channel'], axis = 1, inplace = True)
y = new_data['Milk']

del new_data['Milk']
X_all = new_data
print "new_data upload completed."


# TODO: Split the data into training and testing sets using the given f

try:
    X_train, X_test, y_train, y_test = train_test_split(X_all, y, test_
    print "Data split completed"
except:
    print "Error occured while splitting"

# TODO: Create a decision tree regressor and fit it to the training set

from sklearn.tree import DecisionTreeRegressor
regressor = DecisionTreeRegressor()
regressor.fit(X_train, y_train)
print "Training Complete"

# TODO: Report the score of the prediction using the testing set
# score = None

score = regressor.score(X_test,y_test)

print "The score of the testing set is %s" % score
```

```
new_data upload completed.
Data split completed
Training Complete
The score of the testing set is -0.549497484645
```

Question 2

Which feature did you attempt to predict? What was the reported prediction score? Is this feature relevant for identifying a specific customer?
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.

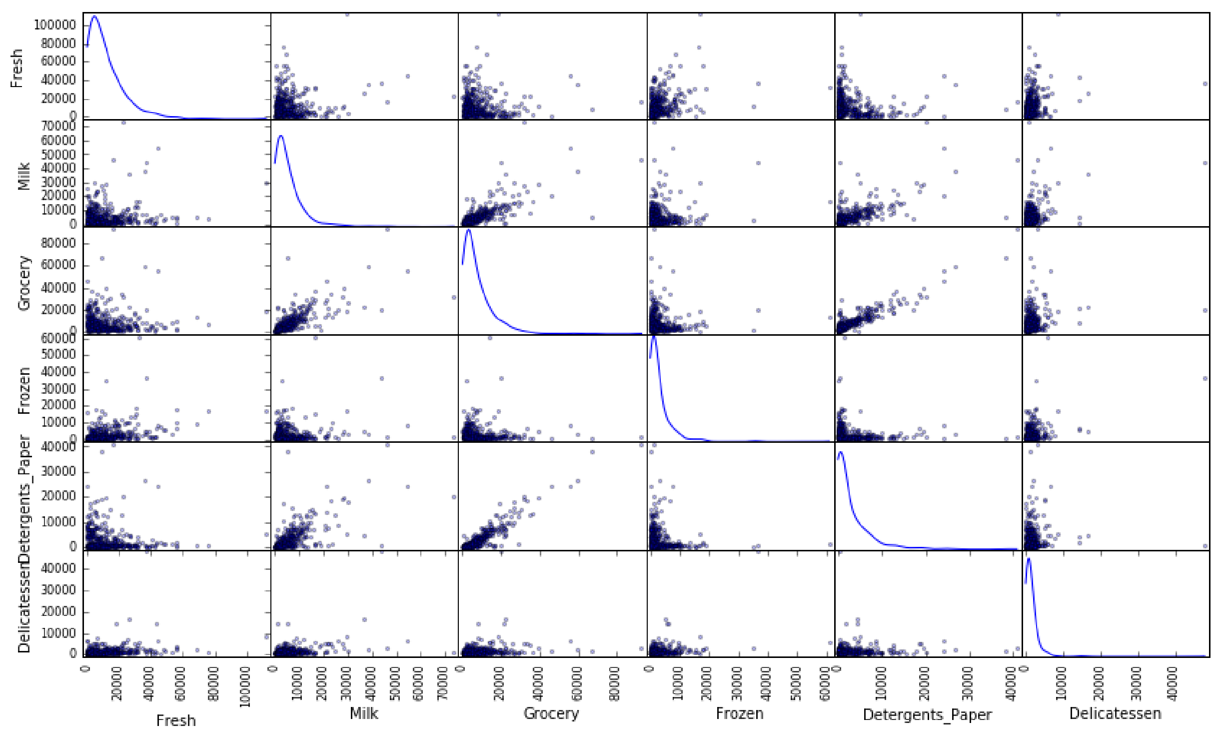
Answer:

I have attempted to predict milk. The reported prediction score is -0.54, which is very low compare the the given model. This shows that the feature is relevatnt to identify specific customer. Thus milk should be included for the dataset.

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:

I can see a slight correlation between grocery and detergent_papers. The same thing is connected between milk and detergent_paper. This connects to my hypothesis of the association between milk and grocery as complements. There is a slight regression on the curve that is linear to each other. Since the data does not have weights placed on the data set, the data is not normally distributed. Most of the datasets are lying by the bottom corner, which shows a certin clustering that goes on with all the data set.

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.

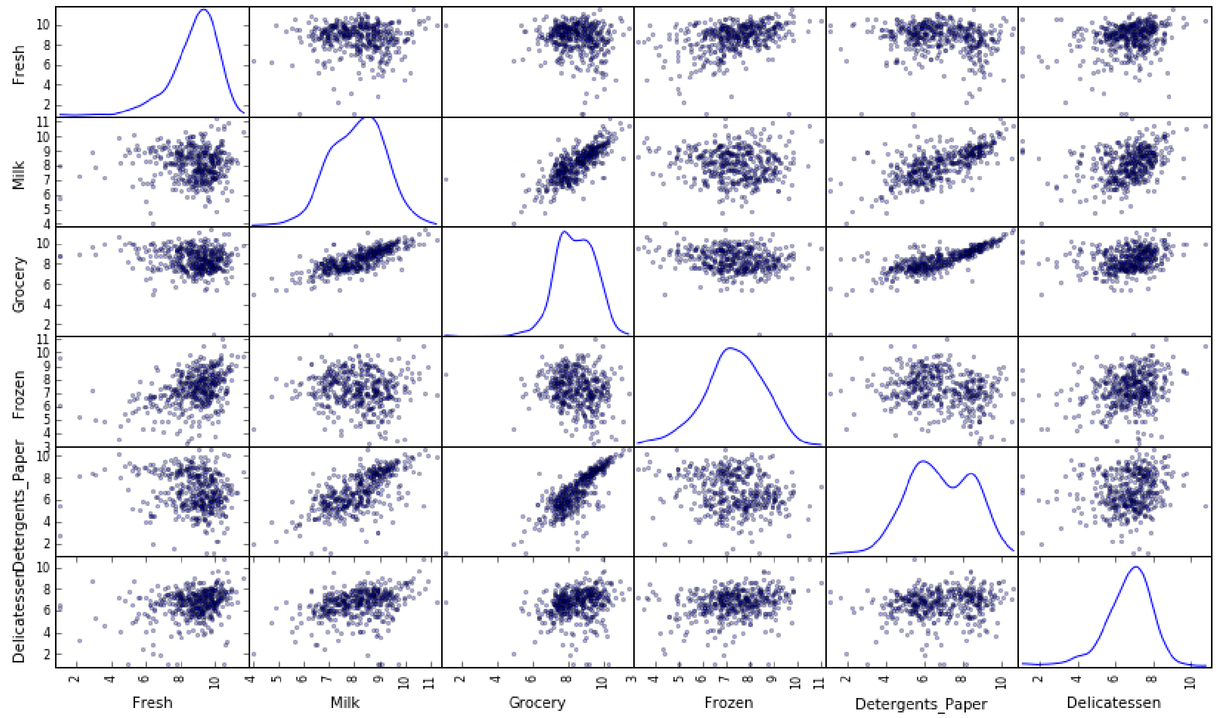
In the code block below, you will need to implement the following:

- 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]:
```
from scipy.stats import boxcox
# TODO: Scale the data using the natural logarithm
log_data = np.log(data)


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

# Produce a scatter matrix for each pair of newly-transformed features
pd.scatter_matrix(log_data, alpha = 0.3, figsize = (14,8), diagonal = '
```



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	9.176784	8.857515	9.256365	6.293419	8.437717	4.174387
1	9.358243	8.959183	9.404590	8.087025	8.991562	8.015988
2	10.164389	7.484369	8.252707	6.458338	5.648974	6.726233

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 [11]:

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

    # TODO: Calculate Q1 (25th percentile of the data) for the given fe
    Q1 = np.percentile(log_data[feature], 25)
    # TODO: Calculate Q3 (75th percentile of the data) for the given fe
    Q3 = np.percentile(log_data[feature], 75)
    # TODO: Use the interquartile range to calculate an outlier step (1
    step = (Q3 - Q1) * 1.5

    # Display the outliers
    print "Data points considered outliers for the feature '{}':".forma
    display(log_data[~((log_data[feature] >= Q1 - step) & (log_data[fea

# OPTIONAL: Select the indices for data points you wish to remove
outliers  = [66, 75]

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

Data points considered outliers for the feature 'Fresh':

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
65	4.442651	9.950323	10.732651	3.583519	10.095388	7.260523
66	2.197225	7.335634	8.911530	5.164786	8.151333	3.295837
81	5.389072	9.163249	9.575192	5.645447	8.964184	5.049856
95	1.098612	7.979339	8.740657	6.086775	5.407172	6.563856
96	3.135494	7.869402	9.001839	4.976734	8.262043	5.379897
128	4.941642	9.087834	8.248791	4.955827	6.967909	1.098612
171	5.298317	10.160530	9.894245	6.478510	9.079434	8.740337
193	5.192957	8.156223	9.917982	6.865891	8.633731	6.501290
218	2.890372	8.923191	9.629380	7.158514	8.475746	8.759669
304	5.081404	8.917311	10.117510	6.424869	9.374413	7.787382
305	5.493061	9.468001	9.088399	6.683361	8.271037	5.351858
338	1.098612	5.808142	8.856661	9.655090	2.708050	6.309918
353	4.762174	8.742574	9.961898	5.429346	9.069007	7.013016
355	5.247024	6.588926	7.606885	5.501258	5.214936	4.844187
357	3.610918	7.150701	10.011086	4.919981	8.816853	4.700480
412	4.574711	8.190077	9.425452	4.584967	7.996317	4.127134

Data points considered outliers for the feature 'Milk':

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
86	10.039983	11.205013	10.377047	6.894670	9.906981	6.805723
98	6.220590	4.718499	6.656727	6.796824	4.025352	4.882802
154	6.432940	4.007333	4.919981	4.317488	1.945910	2.079442
356	10.029503	4.897840	5.384495	8.057377	2.197225	6.306275

```
Data points considered outliers for the feature 'Grocery':
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
75	9.923192	7.036148	1.098612	8.390949	1.098612	6.882437
154	6.432940	4.007333	4.919981	4.317488	1.945910	2.079442

```
Data points considered outliers for the feature 'Frozen':
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
38	8.431853	9.663261	9.723703	3.496508	8.847360	6.070738
57	8.597297	9.203618	9.257892	3.637586	8.932213	7.156177
65	4.442651	9.950323	10.732651	3.583519	10.095388	7.260523
145	10.000569	9.034080	10.457143	3.737670	9.440738	8.396155
175	7.759187	8.967632	9.382106	3.951244	8.341887	7.436617
264	6.978214	9.177714	9.645041	4.110874	8.696176	7.142827
325	10.395650	9.728181	9.519735	11.016479	7.148346	8.632128
420	8.402007	8.569026	9.490015	3.218876	8.827321	7.239215
429	9.060331	7.467371	8.183118	3.850148	4.430817	7.824446
439	7.932721	7.437206	7.828038	4.174387	6.167516	3.951244

```
Data points considered outliers for the feature 'Detergents_Paper':
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
75	9.923192	7.036148	1.098612	8.390949	1.098612	6.882437
161	9.428190	6.291569	5.645447	6.995766	1.098612	7.711101

```
Data points considered outliers for the feature 'Delicatessen':
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
66	2.197225	7.335634	8.911530	5.164786	8.151333	3.295837
109	7.248504	9.724899	10.274568	6.511745	6.728629	1.098612
128	4.941642	9.087834	8.248791	4.955827	6.967909	1.098612

137	8.034955	8.997147	9.021840	6.493754	6.580639	3.583519
142	10.519646	8.875147	9.018332	8.004700	2.995732	1.098612
154	6.432940	4.007333	4.919981	4.317488	1.945910	2.079442
183	10.514529	10.690808	9.911952	10.505999	5.476464	10.777768
184	5.789960	6.822197	8.457443	4.304065	5.811141	2.397895
187	7.798933	8.987447	9.192075	8.743372	8.148735	1.098612
203	6.368187	6.529419	7.703459	6.150603	6.860664	2.890372
233	6.871091	8.513988	8.106515	6.842683	6.013715	1.945910
285	10.602965	6.461468	8.188689	6.948897	6.077642	2.890372
289	10.663966	5.655992	6.154858	7.235619	3.465736	3.091042
343	7.431892	8.848509	10.177932	7.283448	9.646593	3.610918

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:

66 was considered as outliers for Freshness and Delicatessen. The reason may be caused by the establishment purchasing were complementary together.

75 is out for detergent and grocery.

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.

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

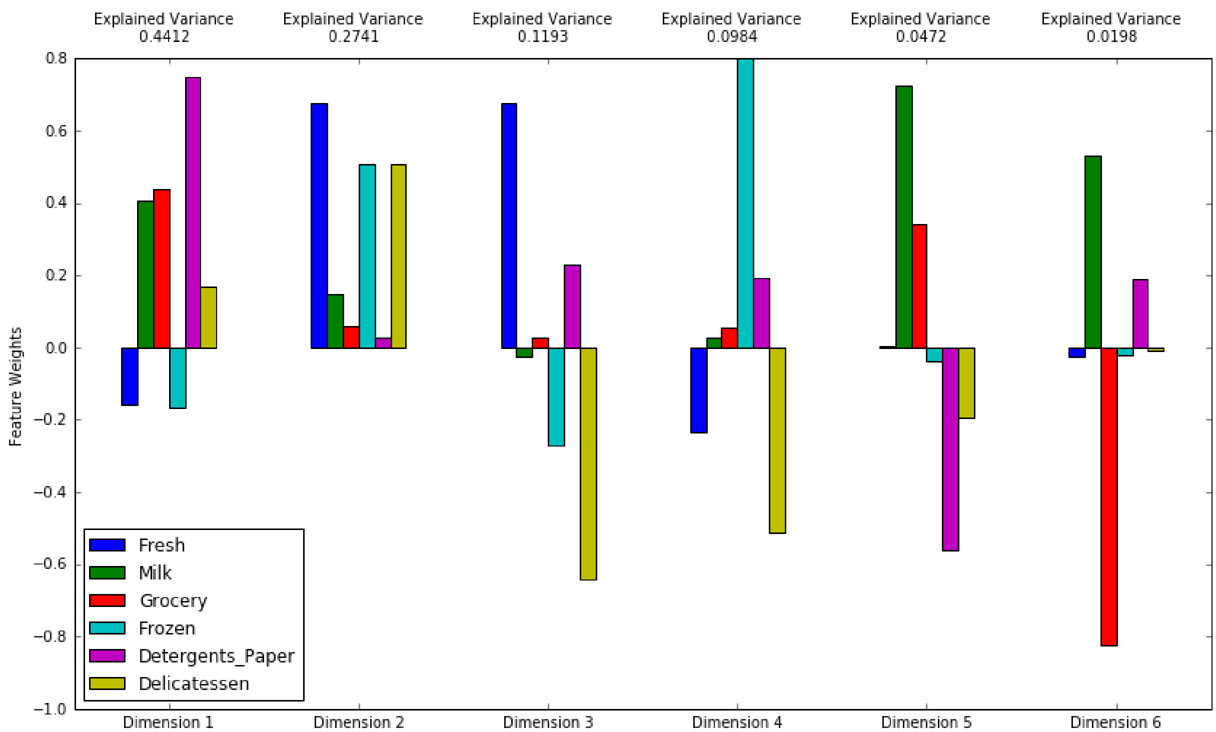
- Import `sklearn.preprocessing.PCA` and assign the results of fitting PCA in six dimensions with `good_data` to `pca`.
- Apply a PCA transformation of the sample log-data `log_samples` using `pca.transform`, and assign the results to `pca_samples`.

In [12]:

```
# TODO: Apply PCA to the good data with the same number of dimensions a
from sklearn.decomposition import PCA
pca = PCA(n_components=6)
pca.fit(good_data)

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

# Generate PCA results plot
pca_results = rs.pca_results(good_data, pca)
```



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:

0.4412 + 0.2741 == 0.7153 vaiance are explained by the first two principal component.

0.4412 + 0.2741 + 0.1193 + 0.0984 == 0.933 variance are explained by the first four components.

The first four dimension is best represented in the customer spending because with 0.933 of variance, all of the features were well maintained while decreasing the dimentionality. If we had only picked the first two dimensions, there would not be enough of the frozen feature that will provide a well represented data.

Additionally, addition a 5th dimention does not strongly benefit the the strenght of the features. with only 0.04 variance, and more higher negative featuring weighting than positive, 4 would be the best dimension to represent customer spending.

Deep Dive to the dimensions

1st dimension: First dimension has predominately Detergent Paper, Grocery, and Milk with less relevant with Delicatessen, Fresh, and Frozen. Having a really high variance on detergent paper shows how dimension 1 would be heavily impacted by Detergent paper. This also means there is a strong correlation between Detergent Paper, Grocey, and Milk, which are all the essentials needed to do in any facilities in the kitchen. Having to first cooked the meals with groceries, milk, and then clean up the facilities with the detergent paper.

2nd dimension Second dimension has dominate feature of "Fresh", "Frozen", and "Delicatessen", and less relveance towards "Detergent_paper." This shows correlation between frozen, fresh, and delicatessen. It can be measured on how fresh products increment would correlate to the increase of Frozen and Delicatessen purchaes. This can be reflected for a customer that would need a short turn around time to produce an edible meal. Mostly associated with day to day busy workers.

3rd dimension Third dimension has dominate feature of "Delicatessen", "Fresh", and less relevant feature in "Milk" and "Grocery." Although Delicatessen is weighted negatively at the third dimension, it is decreasing strongly in the negative-weighted, which is a positive increase in the dimension. With the stronger increase of Fresh is invesely proportional to the decrease of delicastessen. This dimension is reflecting on a potential substitution between Fresh products and the delicatessen products for the customers. In another potential segmentation, this can also reflect as meat eater versus vegetarian.

4th dimension Fourth dimension has dominate feature of "Frozen", as the data is increasd positively on the weight. It also has a strong dominate feature of "Delicatessen", as it is weight strongly negativly. It is less relevant feature in "Milk." The outcome of the "Frozen" feature would heavily dictate the fluctuation of dimension 4. With Frozen that is strongly inversely proportional with "Delicateseen", it can be represented between 2 and 3 dimension, where delicatessen and Fresh is inversely proportional and Fresh and Frozen are directly proportion. This also implies Frozen is inversly prportional to delicatessen.

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 [15]:
```
# Display sample log-data after having a PCA transformation applied
display(pd.DataFrame(np.round(pca_samples, 4), columns = pca_results.in
```

	Dimension 1	Dimension 2	Dimension 3	Dimension 4	Dimension 5	Dimension 6
0	1.5571	-1.2823	2.5510	0.7564	0.4080	0.0705
1	2.3963	1.7346	-0.1557	0.2942	-0.5916	0.0284
2	-1.2864	0.4230	0.9079	-1.2896	0.1345	-0.4091

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 [32]:
```
# TODO: Fit PCA to the good data using only two dimensions
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
pca.fit(good_data)
# TODO: Apply a PCA transformation the good data
reduced_data = pca.transform(good_data)

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

# Create a DataFrame for the reduced data
reduced_data = pd.DataFrame(reduced_data, columns = ['Dimension 1', 'Di
```

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 [33]:
```
# Display sample log-data after applying PCA transformation in two dime
display(pd.DataFrame(np.round(pca_samples, 4), columns = ['Dimension 1'
```

	Dimension 1	Dimension 2
0	1.5571	-1.2823
1	2.3963	1.7346
2	-1.2864	0.4230

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-Mean Clustering K-Mean clustering is a hard cluster, where the clusters do not overlap with each other.

Advantage:

- With large dataset, and small K value, the computation is really fast.
- Produces tighter clusters than heiarachial clusters.
- fast, easy to implement.

Disadvantage:

- Difficult to qualify the clusters
- Fixed K value prohibits a good prediction of a good K.
- Does not work well with non-globular clusters

Gaussian Mixture Model clustering Gaussian Mixture model is a soft cluster, where it may overlap depends on the association between the elements and the cluster.

Advatantage:

- good for classification for static postures and non-temporal pattern recognition

Disadvantage:

- computation can fail if the dimentionality is too high.
- requires to fit in a value for numbers of mixture models.

K-Mean Clustering will be used for customer_segments since we are aware of the using 2 dimensions from PCA to work on the clustering, we know how many clusters there will be.

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 [43]:
```
# TODO: Apply your clustering algorithm of choice to the reduced data
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
clusters_test = [2,3]

def KMeanCluster_test(n_cluster_num):
    clusterer = KMeans(n_clusters=n_cluster_num)
    clusterer.fit(reduced_data)
    # TODO: Predict the cluster for each data point
    preds = clusterer.predict(reduced_data)
    print clusterer
    # TODO: Find the cluster centers
    centers = clusterer.cluster_centers_
    print centers

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

    # TODO: Calculate the mean silhouette coefficient for the number of
    score = silhouette_score(reduced_data, preds)
    print score
    return preds, centers, sample_preds

for n in clusters_test:
    KMeanCluster_test(n)

preds, centers, sample_preds = KMeanCluster_test(2)
```

```
KMeans(copy_x=True, init='k-means++', max_iter=300, n_clusters=2, n_
init=10,
    n_jobs=1, precompute_distances='auto', random_state=None, tol=0.
0001,
    verbose=0)
[[-1.50652716  0.15382567]
 [ 2.17983539 -0.22257457]]
0.421599126619
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)
[[ 1.94807936 -2.24097287]
 [-1.7600919  -0.0029942 ]
 [ 1.61067938  1.20281009]]
0.394494121174
KMeans(copy_x=True, init='k-means++', max_iter=300, n_clusters=2, n_
init=10,
    n_jobs=1, precompute_distances='auto', random_state=None, tol=0.
0001,
    verbose=0)
[[-1.50652716  0.15382567]
 [ 2.17983539 -0.22257457]]
0.421599126619
```

Question 7

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

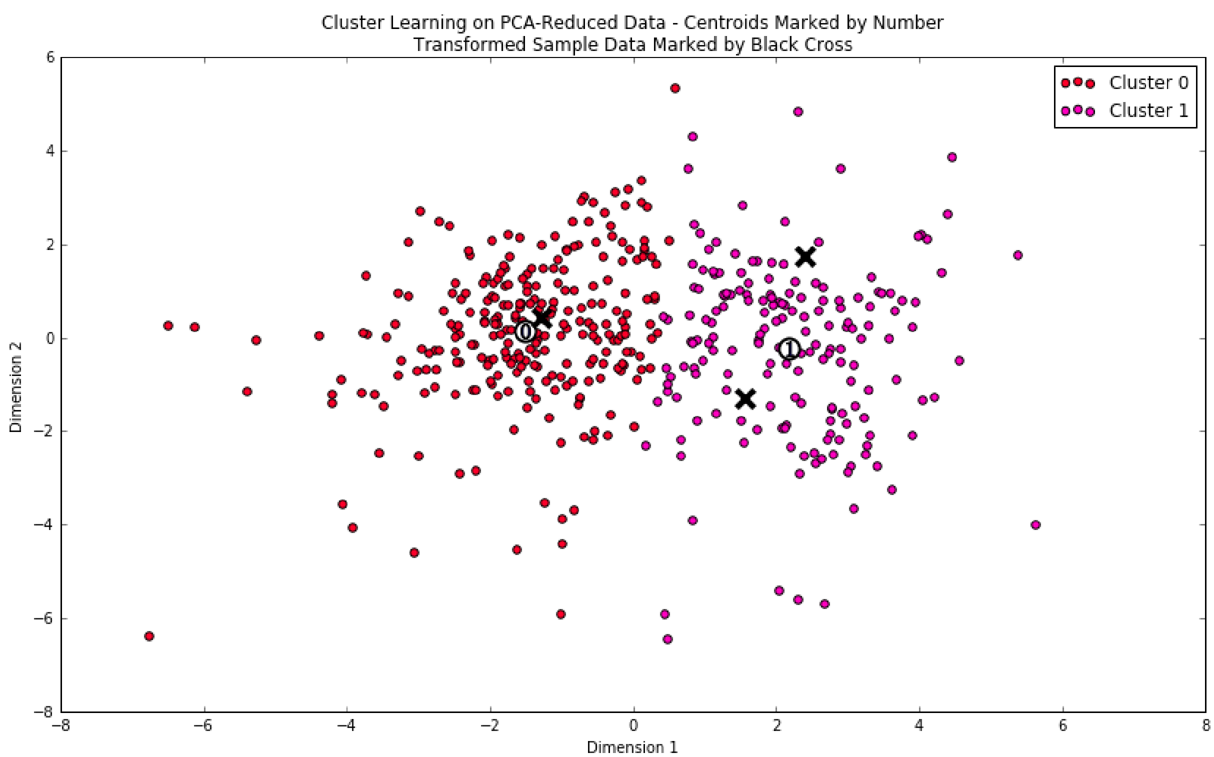
Answer:

The number is 0.42. Number clusters 2 are the best silhouette score.

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 [44]:
```
# 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 [45]:
```
# TODO: Inverse transform the centers
log_centers = pca.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)

# Compare with the breakdown again:
display(data.describe())
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
Segment 0	8843	1871	2448	2062	291	663
Segment 1	3805	7944	12124	925	4537	1018

	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

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 establishment represents restaurants, which is on the left side. It has low on dimension 1, and spreads sporadically in dimension 2. Looking into the visualization breakdown, it would have low "Delicatessen", "Fresh", and "Frozen". This falls into the small or medium restaurant category, where the purchases would not be huge on the client's end to own a restaurant.

Segment 1 represents supermarket, which is on the right side. It is above average in Milk, grocery, and detergent_papers. This falls into a increment in the dimension one. With huge purchses on the items, any customer that is segmented to cluster 1 would be identified as supermarket.

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 [51]:
```
print samples
print pca_samples
display(data.describe())
# Display the predictions
for i, pred in enumerate(sample_preds):
    print "Sample point", i, "predicted to be in Cluster", pred
```

```
   Fresh  Milk  Grocery  Frozen  Detergents_Paper  Delicatessen
0   9670  7027    10471     541              4618            65
1  11594  7779    12144    3252              8035          3029
2  25962  1780     3838     638               284           834
[[ 1.55708075 -1.28234045]
 [ 2.39629417  1.73455055]
 [-1.28639715  0.42299047]]
```

	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

```
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 0
```

Answer: After sample 0 and 1 has compressed into 2 dimensions, it is higher on the first dimension and lower on the 2nd dimension. Reflecting on the visualization, it would be high on detergent paper and low in fresh, frozen, and delicatessen. This falls into the cluster 1 spectrum.

As for sample 2, it has higher on the 2nd dimension and lower on the first. This reflects a higher spend in fresh, frozen, and delicatessen, and lower in detergent paper. This reflects the other model of the cluster, which is cluster 0.

Conclusion

Question 10

Companies often run [A/B tests (https://en.wikipedia.org/wiki/A/B_testing)](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:

Changing the delivery service for the whole sale distributor would not affect all customers equally. Some customers would not need frequent delivery for groceries, and restaurants would want to have a consistent delivery to keep their food fresh.

Through understanding the clusters the customers are a part of, we can test one group of retailers with 5 days a week delivery and another set of retailers with 3 days a week delivery. With the same number of customers in the group, we can test whether if affects the purchasing power of the customer. If the purchases remains consistent for 4 weeks, the whole sales distributor can then change delivery strategy for the cluster.

Question 11

Assume the wholesale distributor wanted to predict some other 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?

Answer:

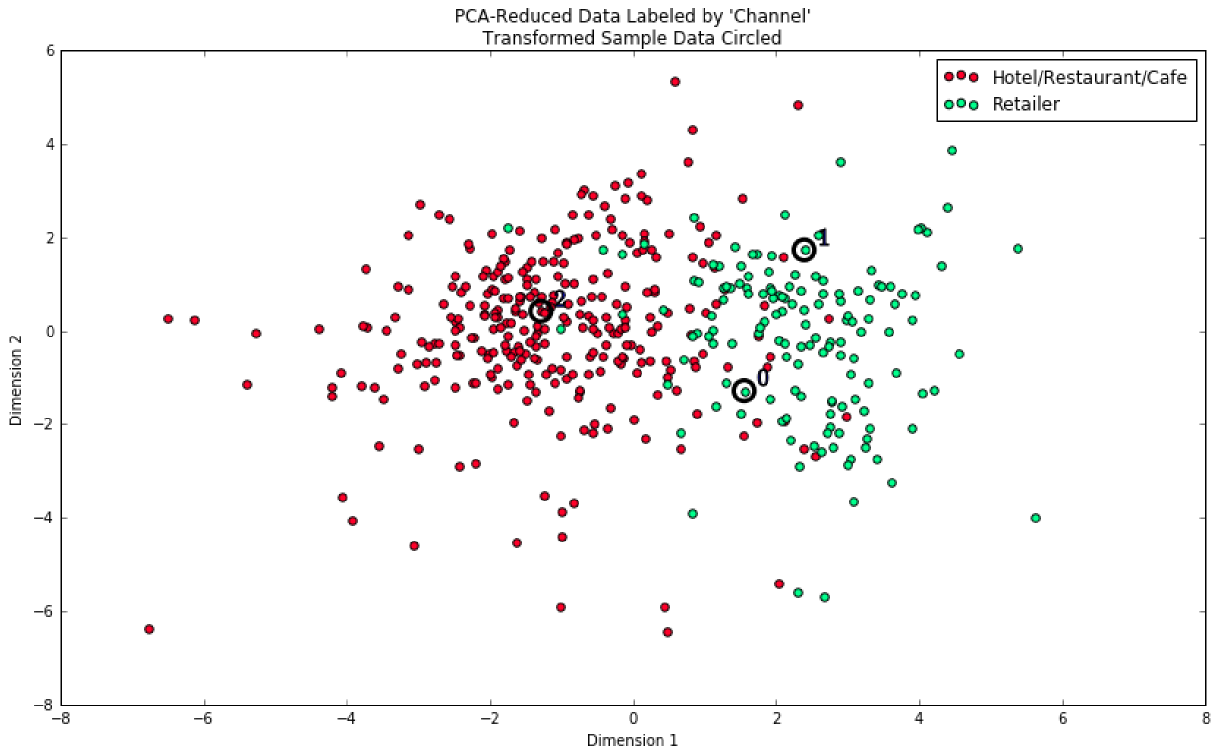
The wholesale distributor, now knowing the clusters of the data, can use supervise learning analysis to classify which customers are part of which establishment. With Support Vector Machine analysis, a new customer having to work with teh whoelsale distributor for a week, can then be segmented to the correct pull of services that can maximize purchasing power of the customer.

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 [18]:
```
# Display the clustering results based on 'Channel' data
rs.channel_results(reduced_data, outliers, 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: A distinctive hyperplane can be drawn between the two clusters. It is very well reflective on the cluster separation from our KMeans clustering. Specfically on 0 dimension 1.

Anything that is on the left side of Dimension 1 would be classified as Hotel/Restaurant/Cafe, and the ones on the right would be Retailer.

It is very well consistent with the definition of our customer segments, as it is well reflective in our K Mean clusters.

> **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.