customer_segments

May 20, 2016

1 Machine Learning Engineer Nanodegree

1.1 Unsupervised Learning

1.2 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.

1.3 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. 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 [3]: # 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.".format(*data.shape
        except:
            print "Dataset could not be loaded. Is the dataset missing?"
```

```
/opt/conda/envs/python2/lib/python2.7/site-packages/matplotlib/font_manager.py:273: UserWarning: Matplot
  warnings.warn('Matplotlib is building the font cache using fc-list. This may take a moment.')

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

1.4 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 [4]: # Display a description of the dataset
        display(data.describe())
```

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

       Detergents_Paper  Delicatessen
count        440.000000    440.000000
mean        2881.493182   1524.870455
std         4767.854448   2820.105937
min            3.000000      3.000000
25%          256.750000    408.250000
50%          816.500000    965.500000
75%         3922.000000   1820.250000
max        40827.000000  47943.000000
```

1.4.1 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 [5]:
```
# TODO: Select three indices of your choice you wish to sample from the dataset
indices = [1, 66, 181]

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

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

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	7057	9810	9568	1762	3293	1776
1	9	1534	7417	175	3468	27
2	112151	29627	18148	16745	4948	8550

1.4.2 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:

Sample 1 represents an average scale store which primarily focusses on selling milk and groceries. Sample 2 represents a small scale store targetting a small region. Sample 3 represents a large scale store mainly focussing on fresh products. It has many daily customers (evident by focus on fresh, milk and forzen products). They might be big scale hotels.

1.4.3 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 [6]:
```
# TODO: Make a copy of the DataFrame, using the 'drop' function to drop the given feature
new_data = data.drop('Detergents_Paper', axis = 1)

# TODO: Split the data into training and testing sets using the given feature as the target
from sklearn.cross_validation import train_test_split
X_train, X_test, y_train, y_test = train_test_split(new_data, data['Detergents_Paper'],
                                                    test_size = 0.25, random_state = 81)

# TODO: Create a decision tree regressor and fit it to the training set
from sklearn.tree import DecisionTreeRegressor
```

```
regressor = DecisionTreeRegressor(random_state = 18).fit(X_train, y_train)

# TODO: Report the score of the prediction using the testing set
score = regressor.score(X_test, y_test)
print score
```

```
0.80160040383
```

1.4.4 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.

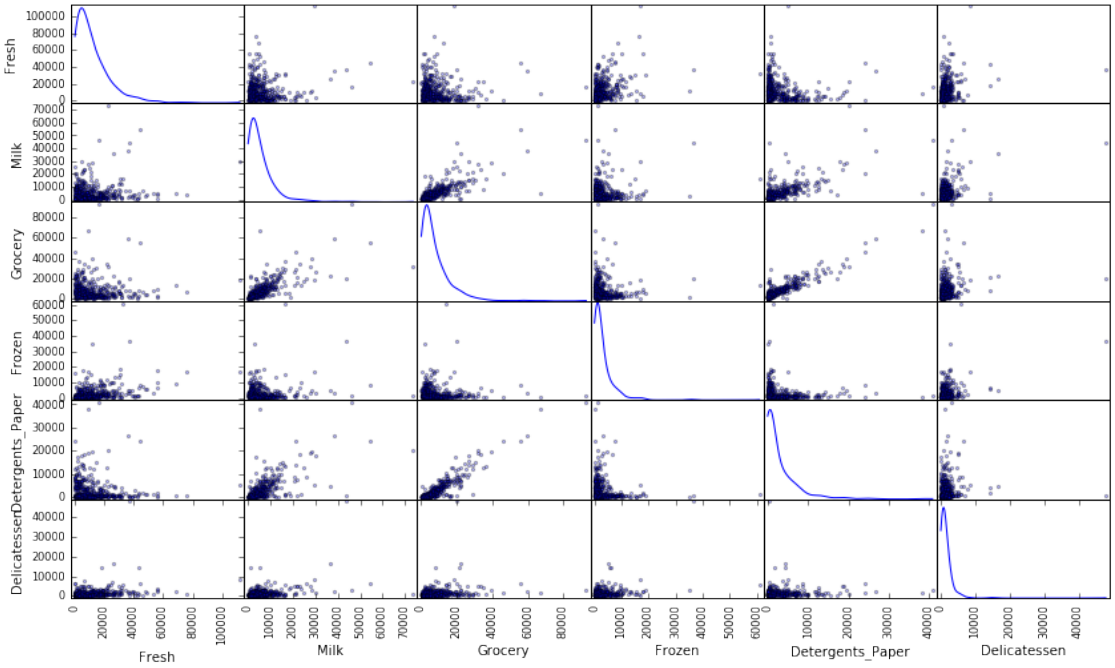
Answer:

I attempted to predict the feature "Detergents_paper" and got an R2 score of 0.8016, which is significant. Therefore we don't really need this feature for identifying customer segments since it can be inferred from the other features.

1.4.5 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 [7]:
```
# Produce a scatter matrix for each pair of features in the data
pd.scatter_matrix(data, alpha = 0.3, figsize = (14,8), diagonal = 'kde');
```



1.4.6 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 variables "Detergents_Paper" and "Grocery" are highly correlated. To a smaller degree, "Detergents_paper" and "Milk" are also correlated, as well as "Milk" and "Grocery". This confirms our suspicions and intuition about the relevance of the "Detergents_Paper" feature. We can get a more precise understanding of the correlations by also computing a correlation matrix, as below. The correlation between "Detergents_Paper" and "Grocery" is 0.925, which is very high. Its correlation with "Milk" is 0.662, and "Milk"'s and "Grocery" 0.729. None of this last two numbers are high enough to discard another feature. The data for all features seems to be positively skewed. We can tell by looking at the KDEs above or by just taking a look at our first description of the data where we saw that for all features the median is significantly lower than the mean.

1.5 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.

1.5.1 Implementation: Feature Scaling

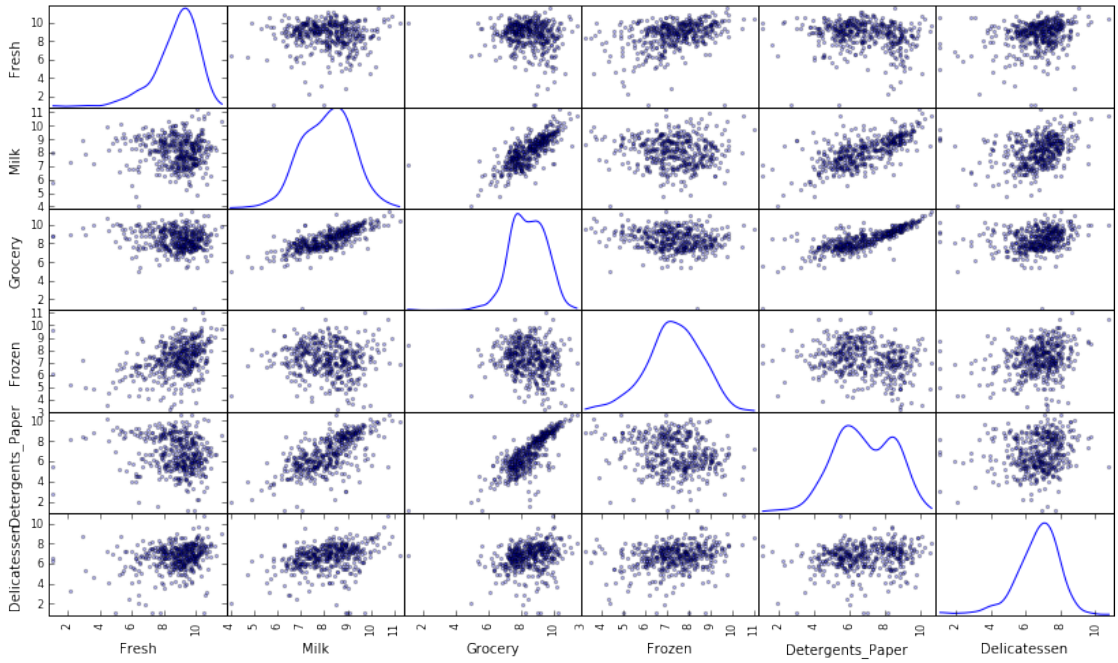
If data is not normally distributed, especially if the mean and median vary significantly (indicating a large skew), it is most often appropriate to apply a non-linear scaling — particularly for financial data. One way to achieve this scaling is by using a Box-Cox test, which calculates the best power 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 [8]:
```
# 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 = 'kde');
```



1.5.2 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 [9]: # Display the log-transformed sample data
        display(log_samples)
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	8.861775	9.191158	9.166179	7.474205	8.099554	7.482119
1	2.197225	7.335634	8.911530	5.164786	8.151333	3.295837
2	11.627601	10.296441	9.806316	9.725855	8.506739	9.053687

1.5.3 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: 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 [10]:
```
# We will store the indices of the outliers in a list
idx = []

# 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 feature
    Q1 = np.percentile(log_data[feature], 25)

    # TODO: Calculate Q3 (75th percentile of the data) for the given feature
    Q3 = np.percentile(log_data[feature], 75)

    # TODO: Use the interquartile range to calculate an outlier step (1.5 times the interquart
    step = 1.5*(Q3-Q1)

    # Display the outliers
    print "Data points considered outliers for the feature '{}':".format(feature)
    display(log_data[~((log_data[feature] >= Q1 - step) & (log_data[feature] <= Q3 + step))])

    # Add the ouliers indices to our list
    idx += log_data[~((log_data[feature] >= Q1 - step) & (log_data[feature] <= Q3 + step))].ind

# Now we can find the indices that show up more than once
duplicates = set([ind for ind in idx if idx.count(ind) > 1])

print "Indices of outliers for more than one feature '{}':".format(sorted(duplicates))

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

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

```
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	\
66	2.197225	7.335634	8.911530	5.164786	8.151333	
109	7.248504	9.724899	10.274568	6.511745	6.728629	
128	4.941642	9.087834	8.248791	4.955827	6.967909	
137	8.034955	8.997147	9.021840	6.493754	6.580639	
142	10.519646	8.875147	9.018332	8.004700	2.995732	
154	6.432940	4.007333	4.919981	4.317488	1.945910	
183	10.514529	10.690808	9.911952	10.505999	5.476464	
184	5.789960	6.822197	8.457443	4.304065	5.811141	
187	7.798933	8.987447	9.192075	8.743372	8.148735	
203	6.368187	6.529419	7.703459	6.150603	6.860664	
233	6.871091	8.513988	8.106515	6.842683	6.013715	
285	10.602965	6.461468	8.188689	6.948897	6.077642	
289	10.663966	5.655992	6.154858	7.235619	3.465736	
343	7.431892	8.848509	10.177932	7.283448	9.646593	

	Delicatessen
66	3.295837

```
109      1.098612
128      1.098612
137      3.583519
142      1.098612
154      2.079442
183     10.777768
184      2.397895
187      1.098612
203      2.890372
233      1.945910
285      2.890372
289      3.091042
343      3.610918


Indices of outliers for more than one feature '[65, 66, 75, 128, 154]':
```

1.5.4 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:

Some of the points are outliers for more than one feature:

65 is an outlier for both Fresh and Frozen,

66 is an outlier for both Fresh and Delicatessen,

75 is an outlier for both Grocery and Detergents_Paper,

128 is an outlier for both Fresh and Delicatessen

154 is an outlier for both Milk, Grocery, and Delicatessen

There is no particular reason why we should exclude these points systematically. However we can turn to the scatterplots for help in identifying which outliers could or should be removed. But before doing that we can already note that some of these outliers have exactly the same value, regardless of which feature they are describing. This value is 1.098612. It actually corresponds to the minimum spending of $3, so there is no need to delete all these points.

Then turning to the scatterplots. There is one point that stands out as a clear candidate for removal. If we look at the scatterplots containing the variable "Grocery" there is one point (the one where the variable takes the minimum value of $3) that is dramatically separated from the rest. We remove this point from our dataset.

1.6 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.

1.6.1 Implementation: PCA

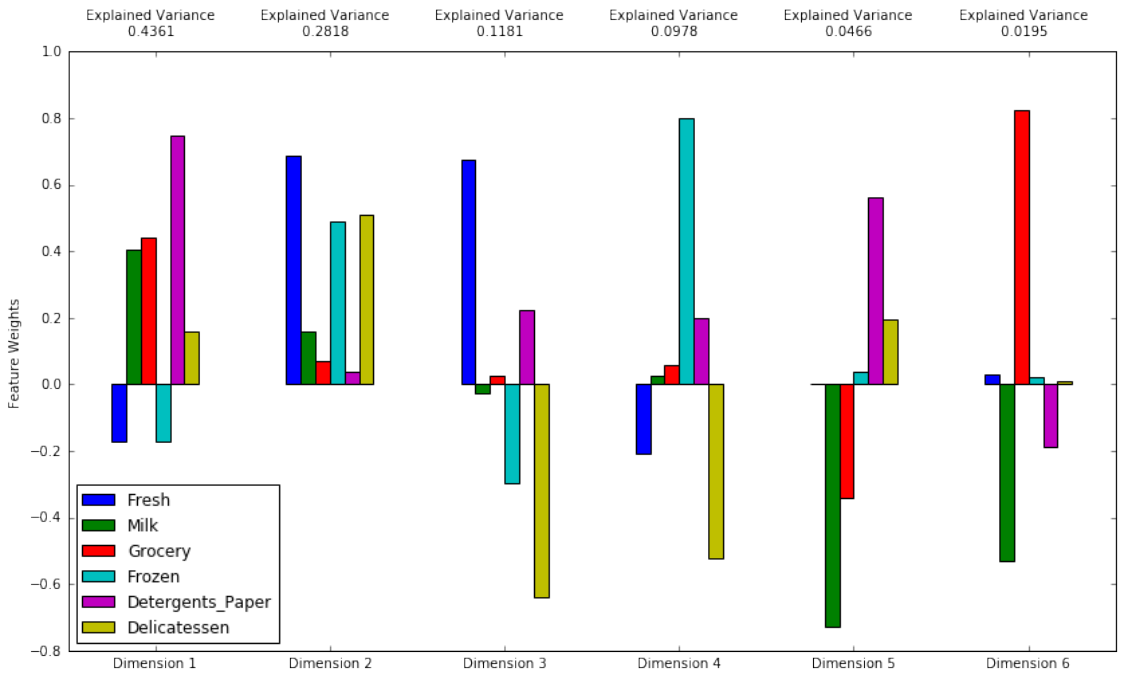
Now that the data has been scaled to a more normal distribution and has had any necessary outliers removed, we can now apply PCA to the `good_data` to discover which dimensions about the data best maximize the variance of features involved. In addition to finding these dimensions, PCA will also report 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 [11]:
```
# TODO: Apply PCA to the good data with the same number of dimensions as features
from sklearn.decomposition import PCA
pca = PCA(n_components=6).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)
```



1.6.2 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 and second component comprises total of 0.719 of the variation. Adding the third and fourth components we can explain 0.9314.

The first component represents how much a customer spends on Detergents and Paper products as well as Groeceries and Milk products.

The second component represents how much a customer spends on Fresh, Frozen, and Delicatessen products. The third can be understood as how much a customer spends on Fresh products and, although less so, Detergent and paper productswhile saving on Delicatessen products and, to a smaller degree, Frozen products. Finally, the fourth PC means how much a customer spends on Frozen foods and (less-so) on Deterents and paper products while saving on Delicatessen.

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

```
   Dimension 1  Dimension 2  Dimension 3  Dimension 4  Dimension 5  \
0       1.7917       0.8595      -0.2033       0.0149      -0.1214
1       1.8523      -7.2829      -1.2890       1.6779       0.4313
2       2.2083       4.8928       0.0703       0.5718      -0.5227

   Dimension 6
0      -0.2118
1       0.2706
2      -0.2050
```

1.6.4 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).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', 'Dimension 2'])

         #reduced_data.plot(x='Dimension 1', y='Dimension 2', kind='scatter')
```

1.6.5 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       1.7917       0.8595
1       1.8523      -7.2829
2       2.2083       4.8928
```

1.7 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.

1.7.1 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:

The advantages of using K-Means clustering is that it always converges (even though it may converge to local minima) and it scales well to large datasets where the number of samples is very large. It is also cheaper than GMM since at each iteration of the algorithm, K-means just has to calculate the mean of the points assigned to a particular cluster on that iteration, whereas GMM has to calculate the parameters of a Gaussian distribution, which is computationally more expensive.

The advantages of using Gaussian Mixture Model clustering are that it is a soft assignement method. That means, that instead of categorically assigning a data point to a cluster it gives it a series of probabilities of having been drawn out of the k Gaussian clusters. Another one of its advantages is that it allows for the different Gaussians to have different variance, adding some more flexibility to our model, whereas K-means tries to split the data into groups of equal variance.

From what we have seen of the data so far there doesn't seem to be a particular reason why K-means would not work, and since in this particular problem we are fine with hard assignments, we opt for the simpler and computationally cheaper option of K-means.

1.7.2 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 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]: from sklearn.cluster import KMeans
         from sklearn.metrics import silhouette_score

         # TODO: Apply your clustering algorithm of choice to the reduced data
         clusterer = KMeans(n_clusters=2, random_state=1).fit(reduced_data)

         # TODO: Predict the cluster for each data point
```

```
preds = clusterer.predict(reduced_data)

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

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

# TODO: Calculate the mean silhouette coefficient for the number of clusters chosen
score = silhouette_score(reduced_data, preds)
```

1.7.3 Question 7

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

In [17]:
```
k_clusters = [2,3,4,5]
sil_scores = []

for k in k_clusters:
    clusterer = KMeans(n_clusters = k).fit_predict(reduced_data)
    score = silhouette_score(reduced_data, clusterer)
    sil_scores.append((k,score))

print sil_scores
```

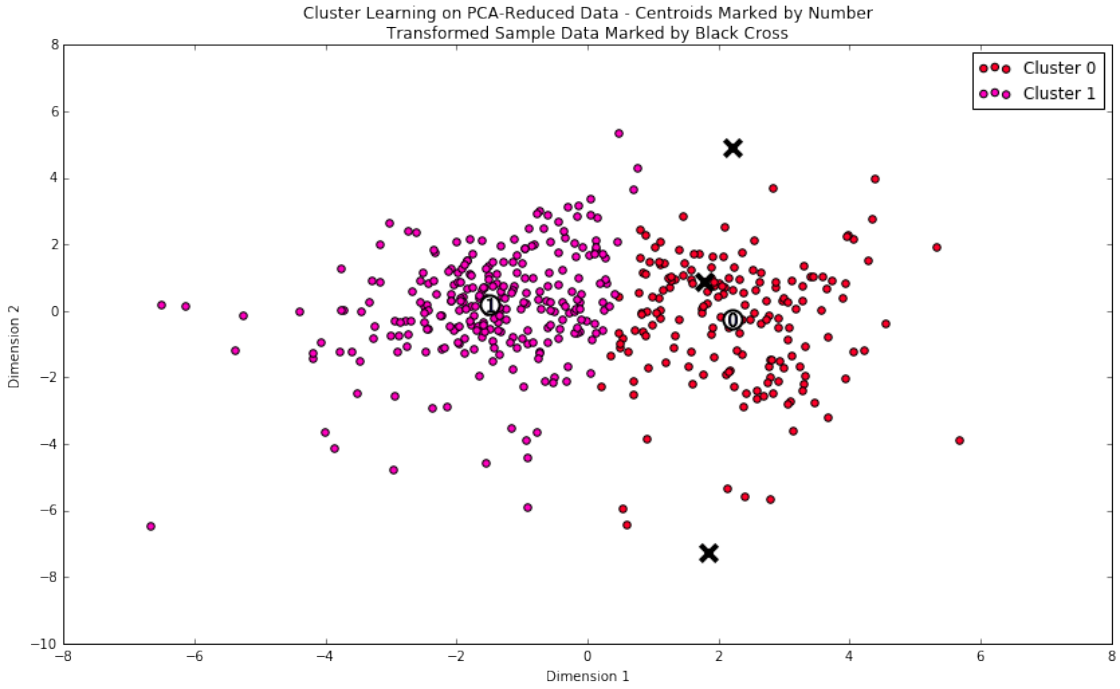
```
[(2, 0.4207957736705138), (3, 0.39415881784761314), (4, 0.33470337800295785), (5, 0.3493837097528088)]
```

Answer:
We obtain the best result for 2 clusters, with a silhouette score of roughly 0.48.

1.7.4 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 [18]:
```
# Display the results of the clustering from implementation
rs.cluster_results(reduced_data, preds, centers, pca_samples)
```



1.7.5 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 [19]: # 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)
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
Segment 0	3532.0	7893.0	12189.0	892.0	4611.0	977.0
Segment 1	8999.0	1899.0	2480.0	2081.0	297.0	676.0

1.7.6 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:

The first cluster, or cluster 0, is centered around customers who spend more than average on Groceries (almost half a standard deviation more), Detergent and Paper, and Milk products. This type of customer also saves on Fresh products (where it spends two thirds of a standard deviation less than average), Frozen (about half a std) and Delicatessen. These trends in spending would correspond to supermarket and grocery stores.

The second cluster, or cluster 1, is centered around clients who spend relatively more in Fresh and Frozen products. Even though the cluster is centered around a point where the spending is below average on all categories, we can still see that this type of customer saves on Milk, Grocery, and Detergent and Paper products, where it spends less than half a std than the average. In the other three categories, the spending is closer to the mean. This cluster would represent restaurants and cafes.

1.7.7 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 [24]: # 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 0
Sample point 1 predicted to be in Cluster 0
Sample point 2 predicted to be in Cluster 0
```

Answer:

Segment 0 best represents sample point 0. Segment 0 best represents sample point 1. Segment 0 best represents sample point 2. The predictions are consistent.

1.8 Conclusion

1.8.1 Question 10

Companies often run A/B tests 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: One of the challenges about running A/B tests is that the control and variation group have to be very similar in order to be able to isolate the effect of what we are testing. Clustering helps us achieve just this. Instead of running an A/B test in with our entire customer base, we can instead run two, one for each cluster. In doing so, not only would we be able to achieve more reliable information on the impact of the change in delivery service, but we would be able to see the difference in acceptance between our two big types of customer.

1.8.2 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:

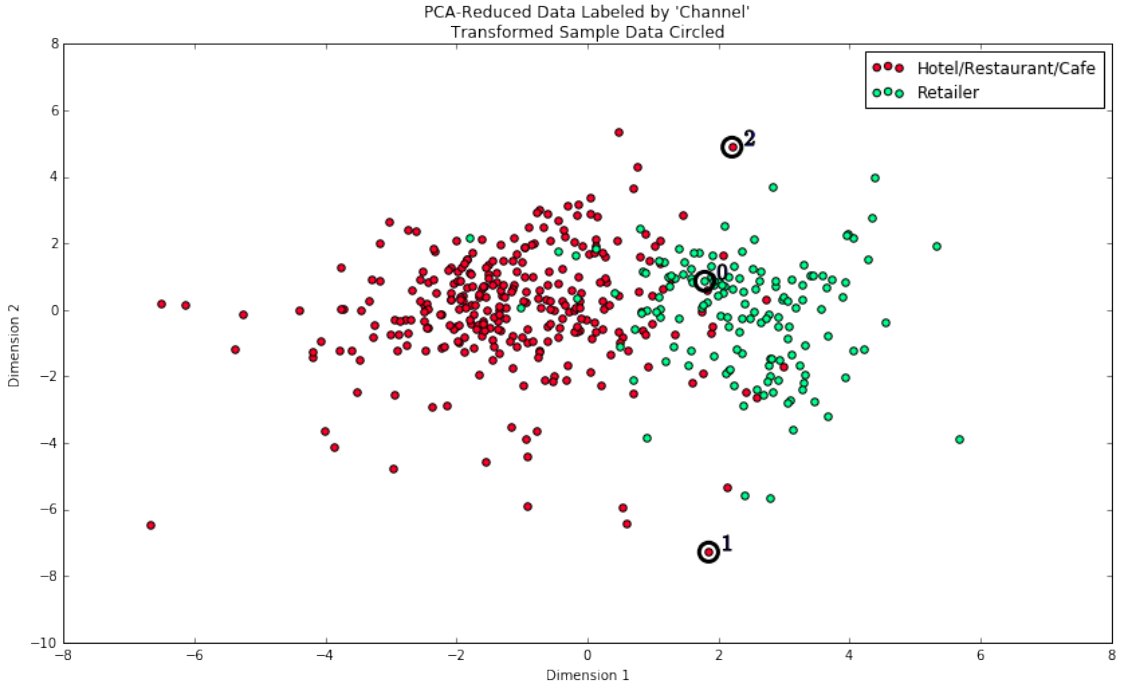
We can now considered the cluster each point belongs to as a new feature which, in addition to our six original variables, could be fed to a supervised learning model.

1.8.3 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 [25]: # Display the clustering results based on 'Channel' data
         rs.channel_results(reduced_data, outliers, pca_samples)
```



1.8.4 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 has succesfully identified the two main customer segments. In light of this new data, we can confirm our initial intuition and description of what we believed were the two main segments. By the nature of our clustering algorithm, in our predictions the two groups are clearly separable and pure. It is not a surprise to see that in reality we have some retailers share characteristics with providers (let's call them that), and some providers share characteristics with retailers, especially near the line dividing the two cluster centers. A soft clustering algorithm would have assigned these points at the boundary a more or less similar probability of belonging to one class or the other. But still, our K-Means with 2 clusters works remarkably 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.