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 [1]:

```
# 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(*dat
a.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 [2]:

```
# Display a description of the dataset
display(data.describe())
```

	Fresh	Milk	Grocery	Frozen	Detergents
count	440.000000	440.000000	440.000000	440.000000	440.00000C
mean	12000.297727	5796.265909	7951.277273	3071.931818	2881.49318
std	12647.328865	7380.377175	9503.162829	4854.673333	4767.85444
min	3.000000	55.000000	3.000000	25.000000	3.000000
25%	3127.750000	1533.000000	2153.000000	742.250000	256.75000C
50%	8504.000000	3627.000000	4755.500000	1526.000000	816.50000C
75%	16933.750000	7190.250000	10655.750000	3554.250000	3922.0000C
max	112151.000000	73498.000000	92780.000000	60869.000000	40827.000C

Implementation: Selecting Samples

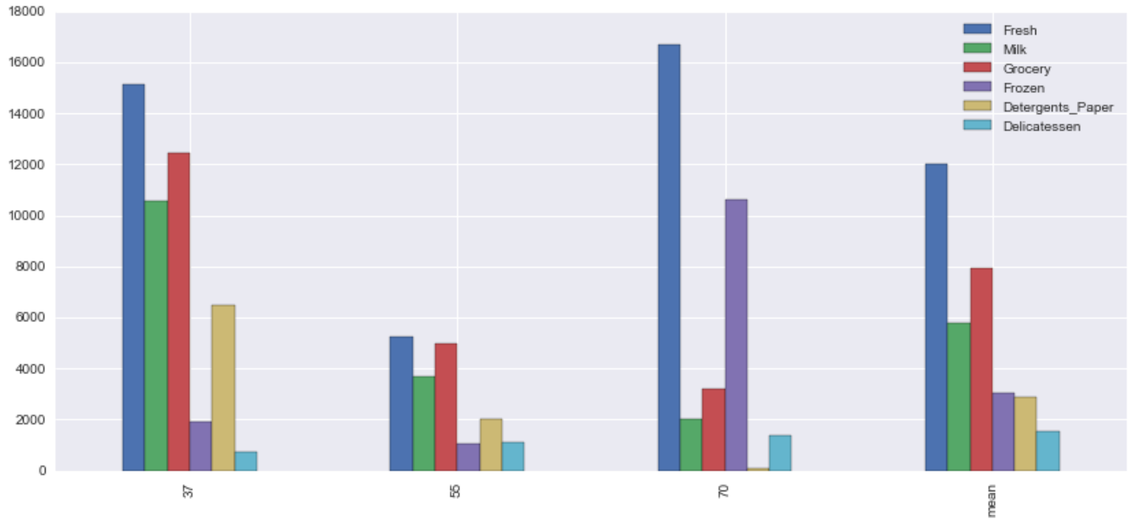
To get a better understanding of the customers and how their data will transform through the analysis, it would be best to select a few sample data points and explore them in more detail. In the code block below, add **three** indices of your choice to the `indices` list which will represent the customers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

In [3]:

```
# TODO: Select three indices of your choice you wish to sample from the dataset
#TotalNum = len(data.index)
#indices = np.random.randint(low = 0, high = TotalNum-1,size = 3)
#print indices

indices = [37,55,70]

# 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)

##  visualise the smample data and comppare it with the mean value of the whole data set
import seaborn as sns
samples_bar = samples.append(data.describe().loc['mean'])
samples_bar.index = indices + ['mean']
_ = samples_bar.plot(kind='bar', figsize=(14,6))
```

Chosen samples of wholesale customers dataset:

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	15168	10556	12477	1920	6506	714
1	5264	3683	5005	1057	2024	1130
2	16705	2037	3202	10643	116	1365



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 0 represents a supermarket.
Reason: The cost on 'Fresh','Milk','Grocery' and 'Detergents_Paper' are higher than the average value. And the value of 'Frozen' is low, which indicates it couldn't be a restaurant. So I guess it represents a large market.

Sample 1 may represent a convenience store.
Reason: The percentage of each feature value is similar to Sample 0. However cost value of all features are samller than mean value of the whole data set. Thus it may represents a tiny store.

Sample 2 represents a restaurant.
Reason: As to sample 2, cost on 'Fresh' and 'Frozen' are much higher than the average. Cost on other features are low. Given these fact, I think sample 2 may provide dishes to people. It is a restaurant.

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 [4]:

```
# TODO: Make a copy of the DataFrame, using the 'drop' function to drop the given feature
new_data = data.drop(['Grocery'],axis = 1)
X_all = new_data
y_all = data['Grocery']
#display(X_all.head())

# TODO: Split the data into training and testing sets using the given feature as the targe
t
from sklearn.cross_validation import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_all, y_all, test_size = 0.25, random
_state=26)

# TODO: Create a decision tree regressor and fit it to the training set
from sklearn.tree import DecisionTreeRegressor
from sklearn.grid_search import GridSearchCV
from sklearn.metrics import make_scorer,r2_score

### use GridSearchCV to pick up the best parameter
parameters = {'max_depth':np.arange(10)+2}
regressor = DecisionTreeRegressor(random_state = 26)
#regressor = DecisionTreeRegressor()

grid_obj = GridSearchCV(regressor, parameters,scoring = 'r2',cv = 5)
grid_obj.fit(X_train,y_train)

regressor = grid_obj.best_estimator_
print regressor.get_params()
#print regressor.score(X_train,y_train)

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

```
{'presort': False, 'splitter': 'best', 'max_leaf_nodes': None, 'min_samples_
leaf': 1, 'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0, 'criterio
n': 'mse', 'random_state': 26, 'max_features': None, 'max_depth': 4}
0.812991249006
```

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.

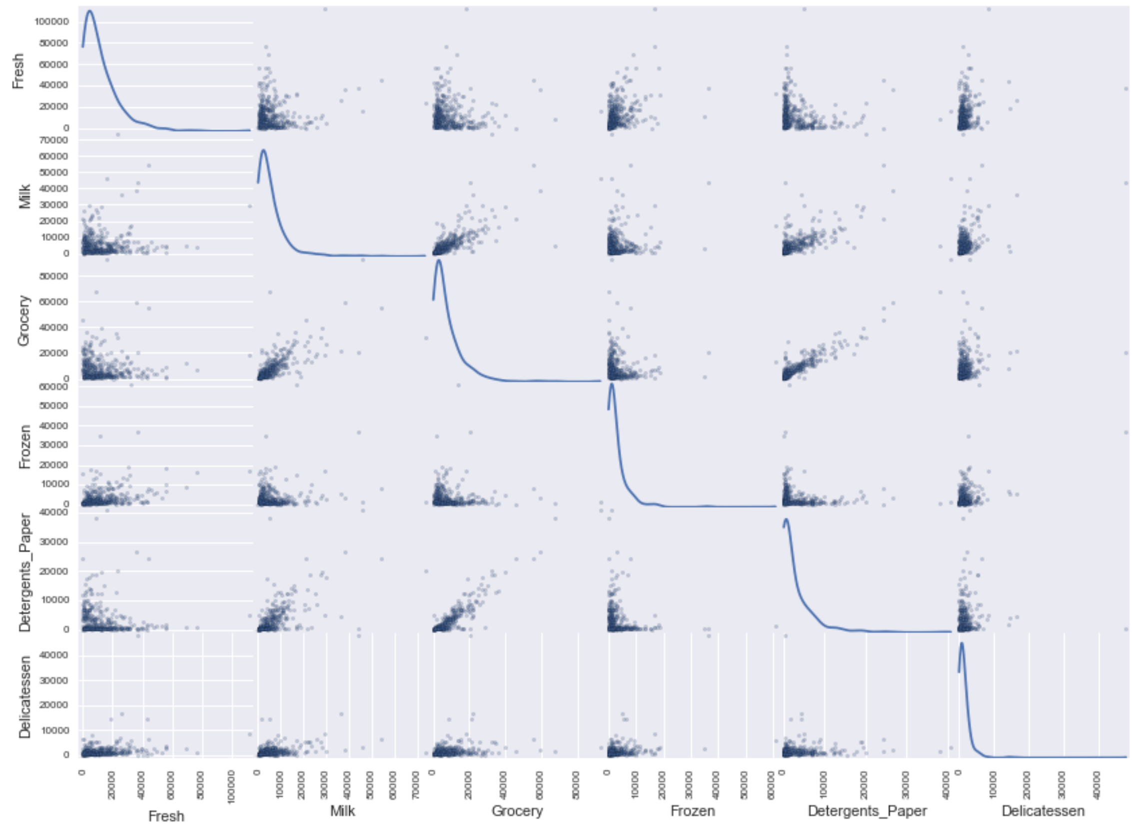
Answer:
I attempt to predict Grocery.
The prediction r2 score on test set is 0.8130.
No, it is not necessary. This feature turns out to be strongly dependent on other features, since the r2 score on test set is high.(The score on training set is almost 1).

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 [5]:

```
# Produce a scatter matrix for each pair of features in the data
pd.scatter_matrix(data, alpha = 0.3, figsize = (14,10), 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:
Yes, I find the feature 'Milk','Grocery' and 'Detergents_Paper' are stronly correlated to each other. This result confirms my statement above.
These data points are not normally distributed. Most of them lie quite close to 0. Peaks of distribution functions are not in the middle of the range.

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

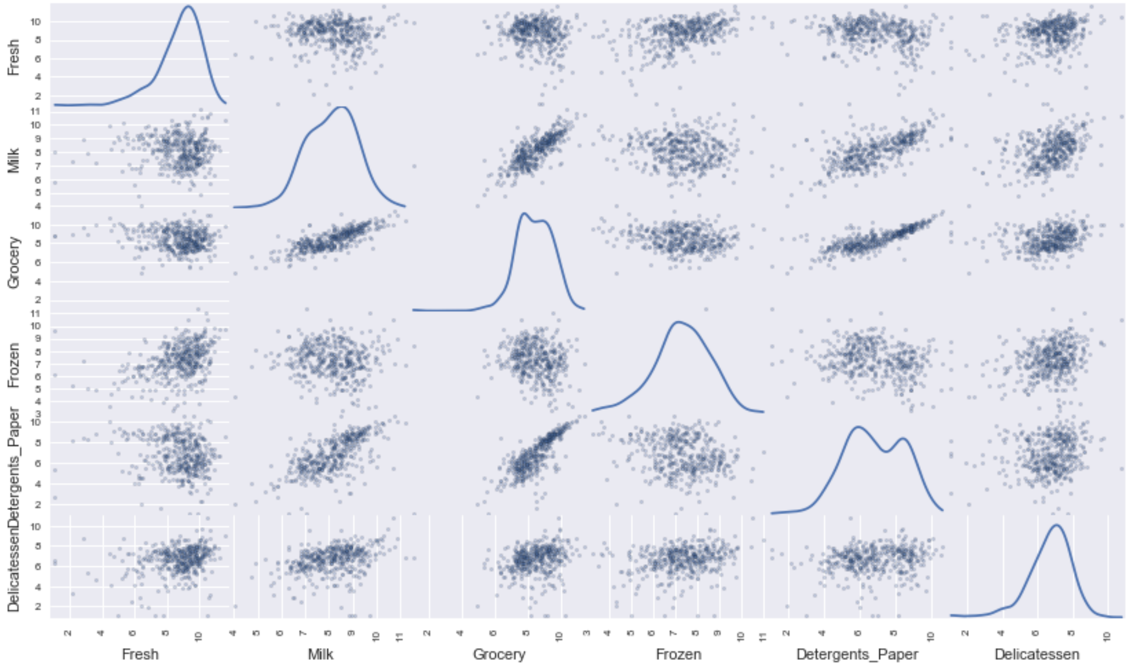
If data is not normally distributed, especially if the mean and median vary significantly (indicating a large skew), it is most often appropriate (http://econbrowser.com/archives/2014/02/use-of-logarithms-in-economics) to apply a non-linear scaling — particularly for financial data. One way to achieve 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 [6]:

```
# 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');
```



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 [18]:

```
# Display the log-transformed sample data
display(log_samples)
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	9.626943	9.264450	9.431642	7.560080	8.780480	6.570883
1	8.568646	8.211483	8.518193	6.963190	7.612831	7.029973
2	9.723463	7.619233	8.071531	9.272658	4.753590	7.218910

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 [20]:

```
# For each feature find the data points with extreme high or low values

all_outliers = np.array([], dtype='int64')

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,axis = 0)

    # TODO: Calculate Q3 (75th percentile of the data) for the given feature
    Q3 = np.percentile(log_data[feature],75,axis = 0)

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

    # Catch the outliers
    outlier_points = log_data[~((log_data[feature] >= Q1 - step) & (log_data[feature] <= Q
3 + step))]
    all_outliers = np.append(all_outliers, outlier_points.index.values.astype('int64'))
    #print all_outliers

    # 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 + ste
p))])

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

# Count the unique elements in the all_outliers array
all_outlier, indices = np.unique(all_outliers, return_inverse=True)
counts = np.bincount(indices)

# Obtain outliers using the counts
outliers = all_outlier[counts>1]
print outliers

# 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	Delicatesse
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	Delicatess
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	Delicatess
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	Delicates
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	10.77776
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

```
[ 65  66  75 128 154]
```

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:
Yes, data points 65,66,75,128,154 are cousidered outliers more than once.
I prefer to remove these outliers. Because we will apply PCA and clustering to the data points. These outliers are far from the mean value, and only a small set of these points may generate very large variance. If not removed, they may affect a lot on the final results.

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.

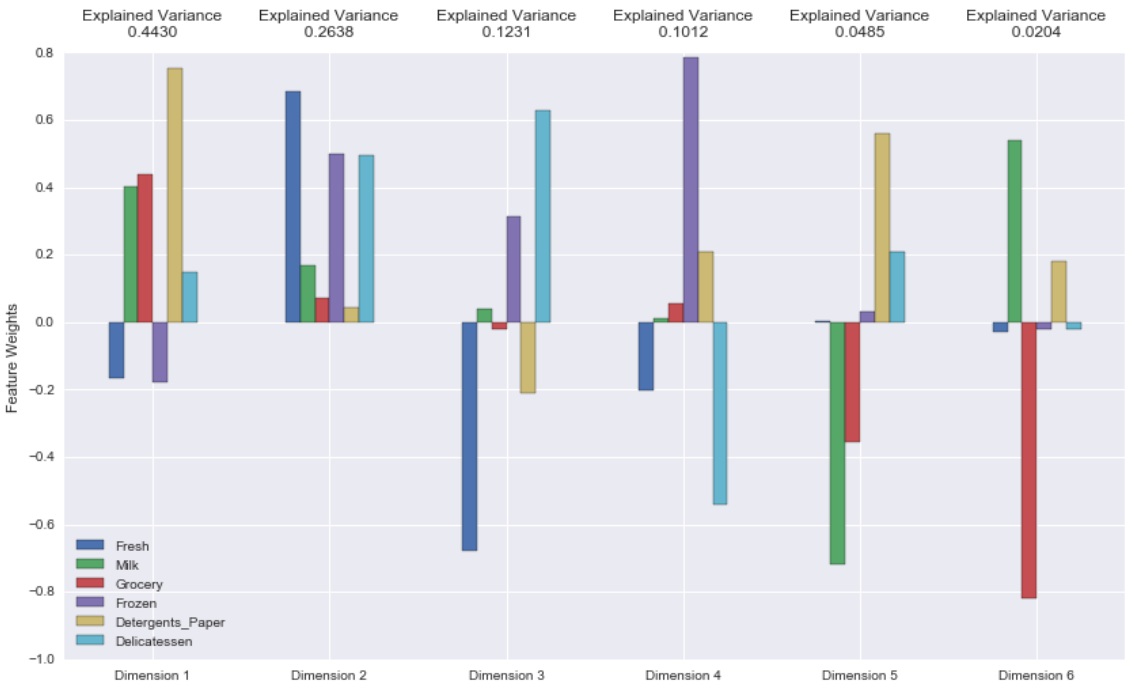
In the code block below, you will need to implement the following:

- 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 [22]:

```
# TODO: Apply PCA to the good data with the same number of dimensions as features
from sklearn.decomposition import PCA
pca = PCA(n_components = len(good_data.columns))
pca = 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)

# obtain the total variances for the first four components
print pca_results['Explained Variance'].cumsum()
```

```
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
```



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 principle component explain 70.68% of data vairance.
The first four of them explain 93.11% of data variance.

For dimension 1 a significant positive weight is placed on Detergents_Paper with meaningful positive weight on Milk and Grocery. This dimension is best categorized by customer spending on retail goods.
For dimension 2, 'Fresh', 'Frozen' and 'Delicatessen' have high positive weight. This indicates that dimension 2 is categorized by spending on food stuff. However the next 2 figures seems confusing. Bar plot for dimension 3 shows a high positve weights for cost on 'Frozen' and 'Delicatessen', which means this dimension is dominate by spending on things to eat, other than fresh food.
For dimension 4, 'Frozen' takes the most positive weight, which means this dimension is mainly categorized by frozen food.

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 [10]:

```
# 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	Dimension 6
0	2.3196	0.5603	0.9189	0.4338	0.2997	0.1984
1	0.8402	-0.4169	-0.0896	-0.1186	-0.4245	0.1404
2	-2.1548	1.8077	-0.5371	0.3283	0.4570	-0.4361

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 [23]:

```
# TODO: Fit PCA to the good data using only two dimensions
pca = PCA(n_components = 2)
pca = 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', 'Dimension 2'])
#pd.scatter_matrix(reduced_data, alpha = 0.6, figsize = (14,8), diagonal = 'kde');
```

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 [24]:

```
# 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	2.1660	0.9897
1	0.8182	-0.0983
2	-2.3404	1.6911

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 algorithm is more simple to use, and its takes small amount of calculation time.
Compared with k-mean, Gaussian Mixture model works with probability distribution, and it can deal with the data points with similar distance to several cluster center. GMM will not diverge.
I should use Gaussian Mixture model. According to the scatter plot figure for reduced data, there is not a clear boundary for each cluster. Lots of points just lie in the middle part.

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)](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 [32]:

```
# TODO: Apply your clustering algorithm of choice to the reduced data
from sklearn.mixture import GMM
from sklearn.metrics import silhouette_score


clusterer = GMM(n_components=2, random_state=26)
clusterer.fit(reduced_data)

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

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

# 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)
print score
```

```
0.411818864386
```

Question 7

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

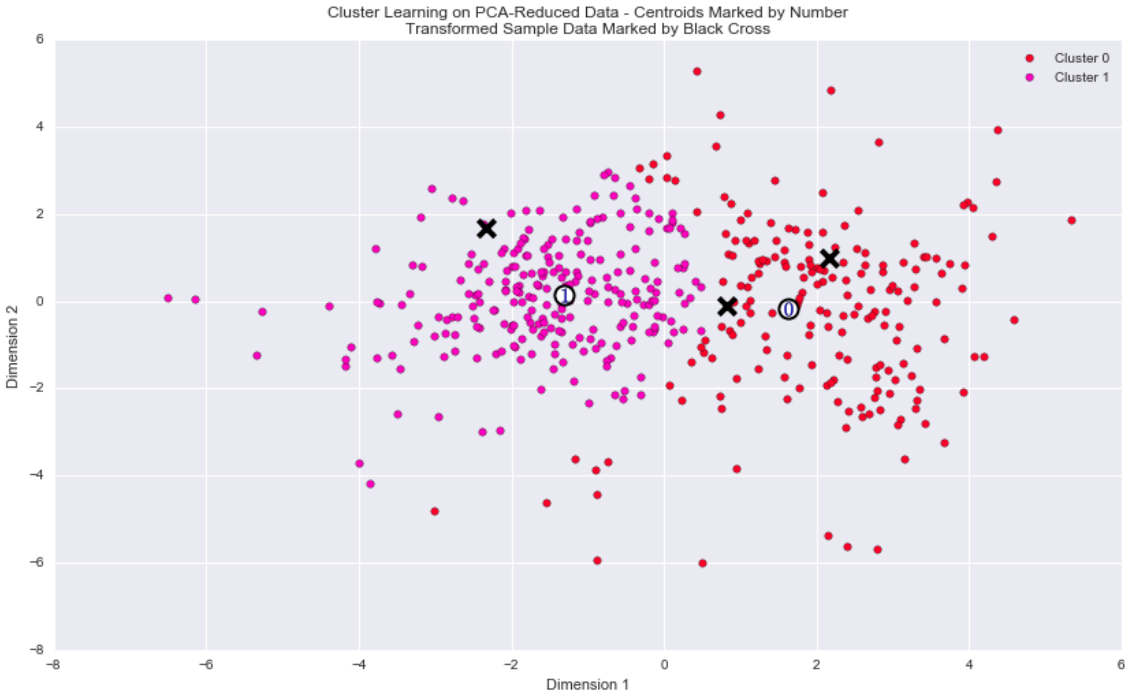
Answer: When n_components = 2, score = 0.4118
n_components = 3, score = 0.3762
n_components = 4, score = 0.3333
n_components = 5, score = 0.2784
n_components = 6, score = 0.2777
Clusters number = 2 provides the best result.

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 [33]:

```
# 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.

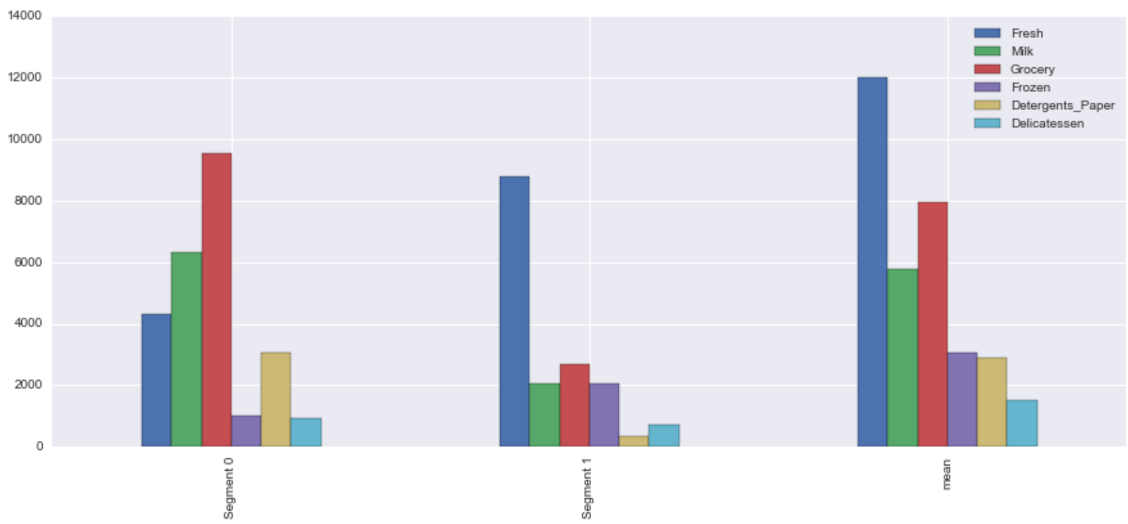
In the code block below, you will need to implement the following:

- 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 [39]:

```
# 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 features of segment centers with mean value of all data
true_centers = true_centers.append(data.describe().loc['mean'])
_ = true_centers.plot(kind='bar', figsize=(15,6))
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
Segment 0	4316.0	6347.0	9555.0	1036.0	3046.0	945.0
Segment 1	8812.0	2052.0	2689.0	2058.0	337.0	712.0



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 represents retailer.
Segment 1 represents restaraunts.
Reason: Compare the features of segment centers with average value of whole data set, we can figure out:

1. For segment 0, the cost on retail goods 'Milk','Grocery' is higher than mean value, and cost on fresh food is much lower. So segment 0 should represents retailer.
2. For segment 1, though the cost on fresh food is bit of lower than mean value, it still takes a much more significant weight in the total cost(summation of all the 6 features), comparing to that for the mean of all data points. Thus I believe it represents restaraunts.

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 [38]:

```
# 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 1
```

Answer:
Sample 0 and 1 belong to cluster 0. Sample 0 belongs to cluster 1.
Reason: Comparing the bar plot of segment centers and those of the sample points I provided in Part 1 of this project, I find that:
For sample 0 and 1, the costs on 'Milk' and 'Grocery' are relatively high, and the costs on 'Fresh' are low. Such condition is similar to segment 0. So I predict they are retailers and belong to Cluster 0.
A notable character of sample points 2 is its ralatively high cost on 'Fresh' and 'Frozen'. Segment 1 also has a high value on 'fresh'. So I predict sample 2 as a restaraunt and belongs to Cluster 1.

The prediction of the code and my guess are consistent.

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:

(previous version)

Pick up N_0 customers from Cluster 0 and N_1 from Cluster 1, where N_1 : N_2 should equal to the ratio of total number of datapoints in Cluster 0 over that in Cluster 1. Then randomly split N_0(N_1) samples from cluster 0(1) into two group, to guarantee finally both experiment group and test group has N_0/2 members from Cluster 0 and N_1/2 members from Cluster 1.
(I mean the experiment group and the control group need to be a mixture of cluster 1 and cluster 2. And the ratio of number of samples from cluster 1 over that from cluster 2 should be the same in these two group. Thanks you for your patient explanation. This time I come up with another idea to run the A/B test. Maybe more sensible)

I will recommend the distributor to run two A/B test. In the first test, we focus on how the change of delivery service affect the customers from cluster 0, the retailers. Randomly choose N_0 samples from cluster 0. Then randomly divide them in two groups, the experiment group and the test group, with equal size.
When finished the first A/B test, we will do a similar test to customers in Cluster 1. In this way, the influence of delivery service change on retailers and markets will be both clear.

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:
Consider the data structure, the prediction of new feature may be different for custermers from various cluster. So I should suggest adding a new colummn of feature 'label', taking values 0 or 1, corresponding to the cluster label we found out previously.

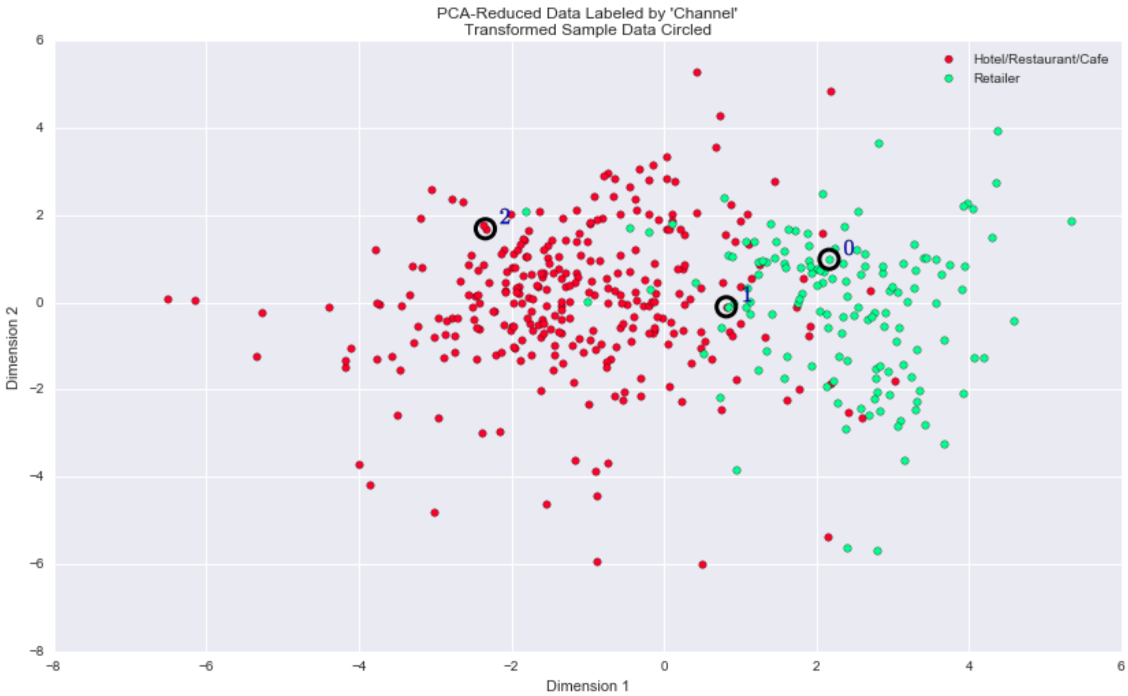
Visualizing Underlying Distributions

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 [40]:

```
# 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:
The clustering algorithm works pretty well. The number of clusters is correct, and the data points are mostly labeled with the correct channel.
Some data points in the middle part goes to the wrong cluster. However, I still regard my customer segments using GMM to be consistent with the real classification. ^_^

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.