Machine Learning Engineer Nanodegree

Unsupervised Learning

Project: 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
from IPython.display import display # Allows the use of display() for DataFrames

# Import supplementary visualizations code visuals.py
import visuals as vs

# Pretty display for notebooks
%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?")
```

```
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_Paper	De
count	440.000000	440.000000	440.000000	440.000000	440.000000	440
mean	12000.297727	5796.265909	7951.277273	3071.931818	2881.493182	152
std	12647.328865	7380.377175	9503.162829	4854.673333	4767.854448	282
min	3.000000	55.000000	3.000000	25.000000	3.000000	3.0
25%	3127.750000	1533.000000	2153.000000	742.250000	256.750000	408
50%	8504.000000	3627.000000	4755.500000	1526.000000	816.500000	965
75%	16933.750000	7190.250000	10655.750000	3554.250000	3922.000000	182
max	112151.000000	73498.000000	92780.000000	60869.000000	40827.000000	479

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 datase
t
indices = [0, 400, 150]

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

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

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	12669	9656	7561	214	2674	1338
1	4446	906	1238	3576	153	1014
2	16225	1825	1765	853	170	1067

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, delis, wholesale retailers, among many others. Avoid using names for establishments, such as saying *"McDonalds"* when describing a sample customer as a restaurant. You can use the mean values for reference to compare your samples with. The mean values are as follows:

- Fresh: 12000.2977
- Milk: 5796.2
- Grocery: 3071.9
- Detergents_paper: 2881.4
- Delicatessen: 1524.8

Knowing this, how do your samples compare? Does that help in driving your insight into what kind of establishments they might be?

Comparing the values of my chosen indices with the mean of the data set -

1. This person seems to spending a lot more on Milk and Groceries than the mean of the data set. Grocery stores like 'Wallmart', 'Staples' and 'Kroger' could be ideal for him.
2. This person seems to be spending very low on Fresh food, milk and groceries. He spends more than 50% on Delicateessen compared to the mean of the data set. So, Stores other than the 0's recommendation like 'Jason'e Deli' would be ideal.
3. This person seems to be spending very high on Fresh food and relative low on other categories compared to the data set. So, stores like 'Subway' and 'Whole Foods' would be recommended for him.

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 gi
ven feature
from sklearn.cross_validation import train_test_split
from sklearn.tree import DecisionTreeRegressor as DTR
from sklearn.metrics import r2_score

Detergents_paper = data['Detergents_Paper']
new_data = data.drop('Detergents_Paper', axis = 1)

#print(data(head))

# TODO: Split the data into training and testing sets(0.25) using the given fe
ature as the target
# Set a random state.
X_train, X_test, y_train, y_test = train_test_split(new_data, Detergents_paper
, test_size = 0.25, random_state = 1)

# TODO: Create a decision tree regressor and fit it to the training set
regressor = DTR(random_state = 1).fit(X_train, y_train)
pred = regressor.predict(X_test)

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

print("Prediction score = ", score)
print("R2 score = ", r2_score(pred, y_test))
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: De
precationWarning: This module was deprecated in version 0.18 in favor of the
model_selection module into which all the refactored classes and functions ar
e moved. Also note that the interface of the new CV iterators are different f
rom that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

```
Prediction score =  0.815241279195
R2 score =  0.773881222242
```

Question 2

- Which feature did you attempt to predict?
- What was the reported prediction score?
- Is this feature 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. If you get a low score for a particular feature, that lends us to beleive that that feature point is hard to predict using the other features, thereby making it an important feature to consider when considering relevance.

- I have attempted to predict 'Detergents_paper'.
- The reported prediction score is approximately 0.815
- Since the feature has high prediction score, this may not be so useful to predict using the other features. Other features can compliment the values of this feature in data prediction.

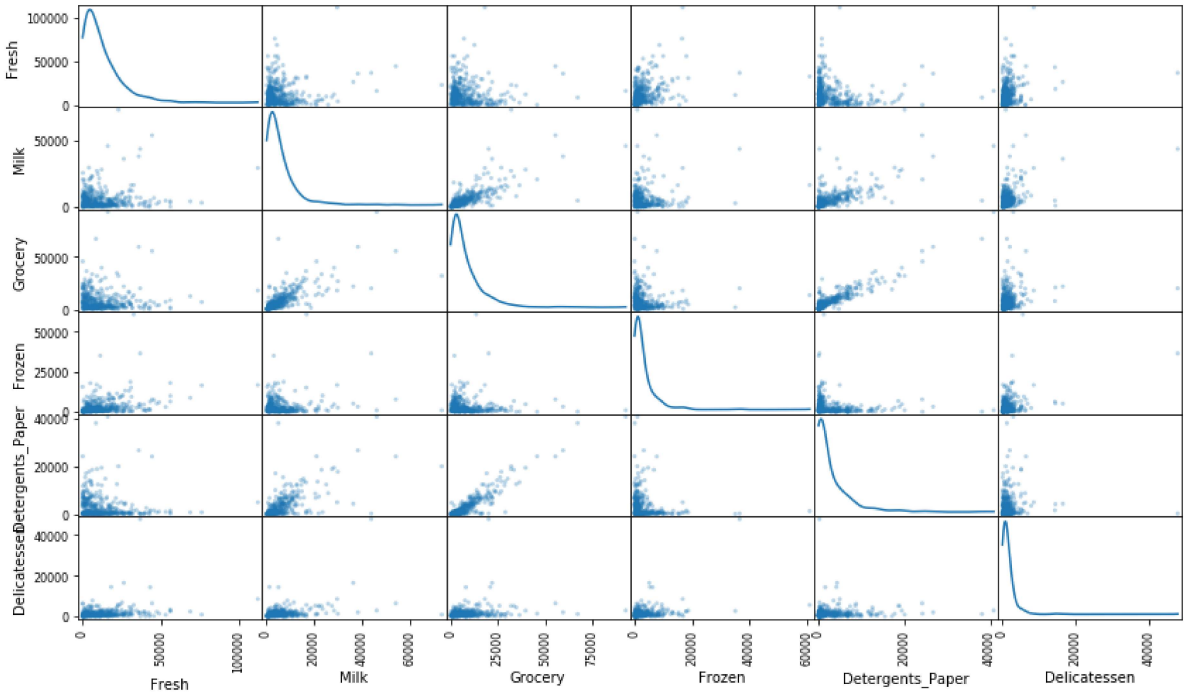
Visualize Feature Distributions

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]:
```
print(data.corr());
```

```
                      Fresh      Milk   Grocery    Frozen  Detergents_Paper  \
Fresh              1.000000  0.100510 -0.011854  0.345881         -0.101953
Milk               0.100510  1.000000  0.728335  0.123994          0.661816
Grocery           -0.011854  0.728335  1.000000 -0.040193          0.924641
Frozen             0.345881  0.123994 -0.040193  1.000000         -0.131525
Detergents_Paper  -0.101953  0.661816  0.924641 -0.131525          1.000000
Delicatessen       0.244690  0.406368  0.205497  0.390947          0.069291

                  Delicatessen
Fresh                 0.244690
Milk                  0.406368
Grocery               0.205497
Frozen                0.390947
Detergents_Paper      0.069291
Delicatessen          1.000000
```

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



Question 3

- Using the scatter matrix as a reference, discuss the distribution of the dataset, specifically talk about the normality, outliers, large number of data points near 0 among others. If you need to sepearate out some of the plots individually to further accentuate your point, you may do so as well.
- 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? You can use corr() (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.corr.html) to get the feature correlations and then visualize them using a heatmap (http://seaborn.pydata.org/generated/seaborn.heatmap.html)(the data that would be fed into the heatmap would be the correlation values, for eg: `data.corr()`) to gain further insight.

- Looks like the data set is well distrubted for different price ranges in all the features. For example - in the scatter plot for Fresh Vs Grocery, the values under 50,000 are well distributed. But, the scale is not similar to all the features, each plot has a different scale and normalizing the data would be beneficial in better understanding the data.
- The first impression looking at the scatter plot is that, there are definitely few features that are highly correlated. I have also confirmed this by using the corr() function on the dataset. Firstly, Detergents_Paper and Groceries seems to have a linear correlation in the scatter plot with a correlation value of 0.92 which is pretty high. Also, Groceries and Milk seem to have similar correlation but not as high as the former, with a correlation value of 0.73.
- It does confirm that Detergents_Paper with higher coefficient of regression can be predicted using other features and specifically Groceries.
- Looking at the marginal distribution of the plots along the diagnol of the plots, the data seems to be definitely skewed. FOr example, for the Delicatessen - Grocery plot the data is cluttered at the origin and not normally distributed along the diagnol.

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.

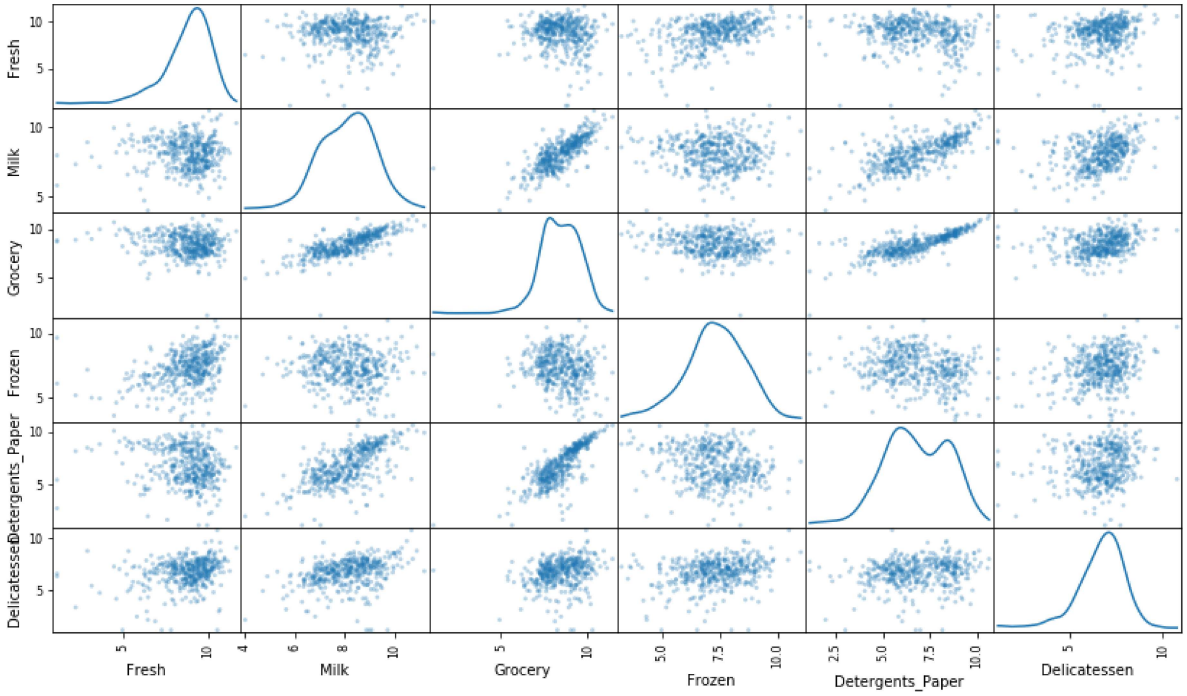
Implementation: Feature Scaling

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

In [7]:
```
# 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.plotting.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 [8]:
```
# Display the log-transformed sample data
display(log_samples)
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	9.446913	9.175335	8.930759	5.365976	7.891331	7.198931
1	8.399760	6.809039	7.121252	8.182000	5.030438	6.921658
2	9.694309	7.509335	7.475906	6.748760	5.135798	6.972606

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
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 time
s the interquartile range)
    step = 1.5 * (Q3 - Q1)

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

# OPTIONAL: Select the indices for data points you wish to remove
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	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 based on the definition above?
- Should these data points be removed from the dataset?
- If any data points were added to the `outliers` list to be removed, explain why.

Hint: If you have datapoints that are outliers in multiple categories think about why that may be and if they warrant removal. Also note how k-means is affected by outliers and whether or not this plays a factor in your analysis of whether or not to remove them.

- Yes, there are outliers for more than one feature based on the definiton above. For example, data with indices 65, 66, 75, 128, and 154.
- No, I don't think they should be definitely removed. They have the potential to reduce the accuracy of the prediciton algorithm also weaken the algorithm without proper tuning the algorithms. But, properly tuning the algorithms should overcome this problem since the outliers are handful compared to the size of the data set.

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

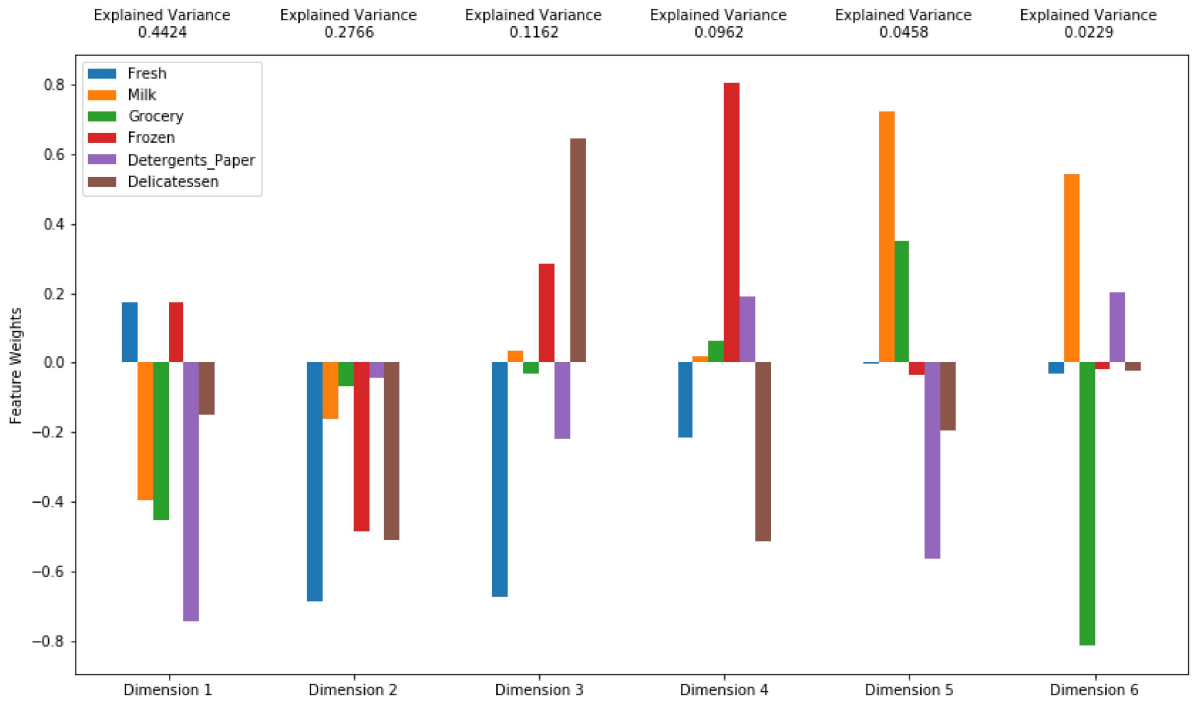
Now that the data has been scaled to a more normal distribution and has had any necessary outliers removed, we can now apply PCA to the `good_data` to discover which dimensions about the data best maximize the variance of features involved. In addition to finding these dimensions, PCA will also report 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 `log_samples` using `pca.transform`, and assign the results to `pca_samples`.

In [23]:
```
# TODO: Apply PCA by fitting the good data with the same number of dimensions
 as features
from sklearn.decomposition import PCA

pca = PCA(n_components = len(good_data.keys())).fit(good_data)

# TODO: Transform log_samples using the PCA fit above
pca_samples = pca.transform(log_samples)

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

print (pca_results['Explained Variance'].cumsum())
```

```
Dimension 1    0.4424
Dimension 2    0.7190
Dimension 3    0.8352
Dimension 4    0.9314
Dimension 5    0.9772
Dimension 6    1.0001
Name: Explained Variance, dtype: float64
```



Question 5

- How much variance in the data is explained ***in total*** by the first and second principal component?
- How much variance in the data is explained by the first four principal components?
- Using the visualization provided above, talk about each dimension and the cumulative variance explained by each, stressing upon which features are well represented by each dimension(both in terms of positive and negative variance explained). 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 individual feature weights.

- Variance in the data by the first principal component is 0.4424. Variance in the data by the first and second principal component is 0.719.
- Variance in the first four principal components is 0.9314.
- The first dimension has high variance for Detergents_Paper, Grocery and Milk. We can infer that these 3 components are much closely related and it determines the relation between the 3. Thus, this dimension could classify the data based on establishments that used these quantities significantly compared to the rest. May be establishments like Restaurants can be considered in this case. The second dimension shows higher correlation between Fresh, Frozen and delicatessen. This means that for a change in this dimension value, the values for these components tend to vary significantly. So, this could possibly indicate expenditure on coffee shops like Starbucks or Cafe Coffee day. These categories can form one cluster.
  The third dimension has very high feature weights for delicatessen and fresh food. This could imply a category where money is spent mostly on fresh food and delicatessen. Such establishments, possible like Subway are indicated with this dimension and change in the dimension reflects on the expenditure of these two categories. The fourth dimension indicates high feature weights for frozen and delicatessen. So establishments like Pizza hut are considered are indicated by this dimension. A change is the value for this dimension is tend to vary the values for the expenditure on these categories.

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 [11]:
```
# 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	-1.7510	-0.0705	-0.9118	-1.7265	0.2741	0.3984
1	2.4819	0.0446	1.0212	0.2059	-0.4992	-0.0051
2	1.9364	-0.3120	-0.2373	-1.1971	0.1116	0.0938

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 results to `reduced_data`.
- Apply a PCA transformation of `log_samples` using `pca.transform`, and assign the results to `pca_samples`.

In [12]:
```
# TODO: Apply PCA by fitting the good data with only two dimensions
pca = PCA(n_components = 2).fit(good_data)

# TODO: Transform the good data using the PCA fit above
reduced_data = pca.transform(good_data)

print(len(reduced_data))

# TODO: Transform log_samples using the PCA fit above
pca_samples = pca.transform(log_samples)

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

print(pca_samples)
```

```
440
[[-1.75098532 -0.07051523]
 [ 2.48187721  0.04463689]
 [ 1.93642019 -0.31204352]]
```

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 [13]:
```
# Display sample log-data after applying PCA transformation in two dimensions
display(pd.DataFrame(np.round(pca_samples, 4), columns = ['Dimension 1', 'Dime
nsion 2']))
```

	Dimension 1	Dimension 2
0	-1.7510	-0.0705
1	2.4819	0.0446
2	1.9364	-0.3120

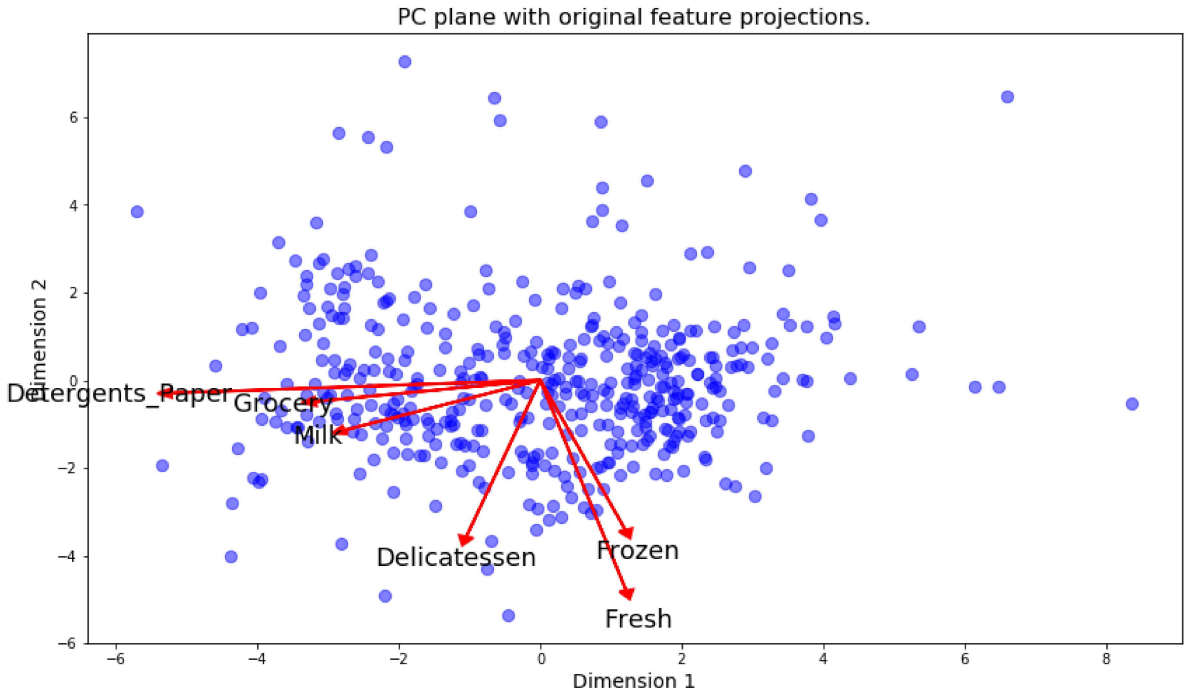
Visualizing a Biplot

A biplot is a scatterplot where each data point is represented by its scores along the principal components. The axes are the principal components (in this case `Dimension 1` and `Dimension 2`). In addition, the biplot shows the projection of the original features along the components. A biplot can help us interpret the reduced dimensions of the data, and discover relationships between the principal components and original features.

Run the code cell below to produce a biplot of the reduced-dimension data.

In [14]:
```
# Create a biplot
vs.biplot(good_data, reduced_data, pca)
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x28f93d96b38>



Observation

Once we have the original feature projections (in red), it is easier to interpret the relative position of each data point in the scatterplot. For instance, a point the lower right corner of the figure will likely correspond to a customer that spends a lot on `'Milk'`, `'Grocery'` and `'Detergents_Paper'`, but not so much on the other product categories.

From the biplot, which of the original features are most strongly correlated with the first component? What about those that are associated with the second component? Do these observations agree with the pca_results plot you obtained earlier?

Detergent_Paper, Grocery and Milk are most strongly correlated with the first component. Fresh, Frozen and Delicatessen are associated with second component. Yes, these observationsa agree with the pca_results plot that we obtained earlier.

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?

Hint: Think about the differences between hard clustering and soft clustering and which would be appropriate for our dataset.

- When the number of clusters to find is known, K-Means clustering algorithm works great in identifying the clusters. The clustering here is based on the inter-cluster distance and the center of the clusters which is logically a great way of grouping data-points. The higher affinity data points should always be associated together and it is a simple algorithm to perform clustering. If the variables are huge, K-means most of the times computes faster when the number of clusters is small. Strongly affinated clusters are formed due to k-means
- Guassian Mixture Model clustering algorithm is a very flexible algorithm. K-means is only a special case of guassian. Gaussian Mixture model works well when the classification is based on static postures and non-temporal pattern recognition.
- Considering that there might be some hidden variables to classify the data and the data to be classified doesn't seem to straight forward to obtain a spherical cluster, which k-means would produce, I would go with Guassian Mixture Model. Also, it maximizes only the likelihood of the data and won't bias the means towards zero or depend on the cluster size. Resources - https://www.quora.com/What-are-the-advantages-of-K-Means-clustering (https://www.quora.com/What-are-the-advantages-of-K-Means-clustering) https://www.quora.com/What-are-the-advantages-to-using-a-Gaussian-Mixture-Model-clustering-algorithm (https://www.quora.com/What-are-the-advantages-to-using-a-Gaussian-Mixture-Model-clustering-algorithm) http://scikit-learn.org/stable/modules/mixture.html (http://scikit-learn.org/stable/modules/mixture.html)

Implementation: Creating Clusters

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

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

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

In [15]:
```
# TODO: Apply your clustering algorithm of choice to the reduced data
from sklearn.mixture import GaussianMixture as GM
from sklearn.metrics import silhouette_score
clusterer = GM(n_components = 2).fit(reduced_data)

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

# TODO: Find the cluster centers
centers = clusterer.means_
print(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 c
hosen
score = silhouette_score(reduced_data, preds)

print(score)
```

```
[[ 1.15035577 -0.25960471]
 [-2.26849647  0.51193933]]
0.409968324528
```

Question 7

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

- 2 n_components - 0.410366734627
- 3 n_components - 0.418397819056, 0.412196880541, 0.233042743965
- 4 n_components - 0.307813536026
- 10 n_components - 0.31848292729

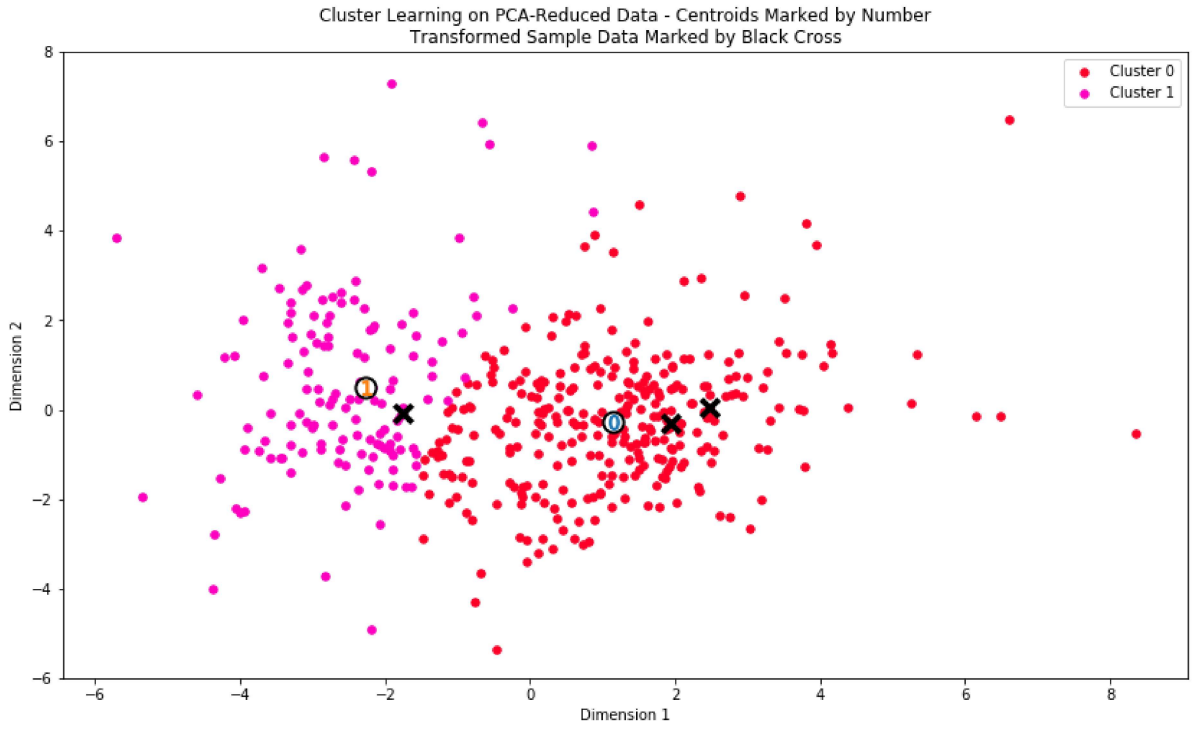
Out of these, n_components = 3 has the best silhouette score. For the same sample and same number of clusters, silhouette score has shown three different scores. But, the maximum turns out to be from this number of components and since it is inconsistent. I would rather consider n_components = 2 as the best cluster number.

Also, interesting the visualization for n_components = 3 detects all the outliers. May be we can use this cluster in detecting outliers in some other problems.

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 [16]:
```
# Display the results of the clustering from implementation
vs.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 [17]:
```
# 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	9029.0	2229.0	2798.0	2051.0	380.0	754.0
Segment 1	2939.0	7576.0	12536.0	781.0	4702.0	848.0

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(specifically looking at the mean values for the various feature points). 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'`. Think about what each segment represents in terms their values for the feature points chosen. Reference these values with the mean values to get some perspective into what kind of establishment they represent.

- All the values in segments 0 are much lower than the mean values of the raw data used intially. It could basically mean that these people could be from a lower income background and could be buying from establishments that offer cheaper prices than the rest of the establishments. Or it could also mean that they spend less on all of these categories and some one else might be taking care of this for them. It could be McDonalds or Wallmart.
- People belonging to segment 1 seem to spend more/less on Milk, Groceries and Detergents_paper which we found to be high correlated and this could be related to establishments where they sell regular day-to-day needs like Kroger, Wallmart or Staples etc. The segment 1 identifies people who are either spending very high on these categories or very less.

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 [18]:
```
# Display the predictions
for i, pred in enumerate(sample_preds):
    print ("Sample point", i, "predicted to be in Cluster", pred)
```

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

- Sample point 0 best represents Cluster 1. It is fair to consider that because Milk, Grocery and Detergents_Paper seem to be higher than values of the mean and this could mean that they would go to establishments like Kroger (Grocery stores) as they spend high on these categories.
- Sample 1 and 2 best represent Cluster 0. Because both the samples seems to spend low on the former 3 categories and spend relatively more on Fresh/Frozen food.

Conclusion

In this final section, you will investigate ways that you can make use of the clustered data. First, you will consider how the different groups of customers, the ***customer segments***, may be affected differently by a specific delivery scheme. Next, you will consider how giving a label to each customer (which *segment* that customer belongs to) can provide for additional features about the customer data. Finally, you will compare the ***customer segments*** to a hidden variable present in the data, to see whether the clustering identified certain relationships.

Question 10

Companies will often run A/B tests (https://en.wikipedia.org/wiki/A/B_testing) when making small changes to their products or services to determine whether making that change will affect its customers positively or negatively. The wholesale distributor is considering changing its delivery service from currently 5 days a week to 3 days a week. However, the distributor will only make this change in delivery service for customers that react positively.

- How can the wholesale distributor use the customer segments to determine which customers, if any, would react positively to the change in delivery service?*

Hint: Can we assume the change affects all customers equally? How can we determine which group of customers it affects the most?

- Customers belonging to the cluster 0 will not have major effect if they delivery is for Milk, Grocery and Detergent_Papers. As they spend low than the average of the data ion these categories. In case of fresh and frozen it would cause a real problem to them as they spend more on these food and they need to delivered on daily basis. However if discussed about Delicatessen, one cannot determine any generalization from it.
- Similarly for cluster 1, these customers may react negatively if the delivery service is reduced to 3 days in terms of Milk, Grocery and Detergents_Paper as they spend relatively high on these quantities. But, unlike fresh food, requirements can be ordered in advance as they the food in these categories stay good for long. So, although they spend high on 3 mentioned categories, it should not cause adverse problems even if the delivered is reduced in these 3 categories. In terms of delicatessen it is same as mentioned above. A/B testing, sometimes called as 'split testing' works by considering changes in the variants that can cause a major impact on classifying the variants. But, it may not always be fruitful in considering this tests, especially in cases like the problem. Here, the whole sale distributor wants to reduce the serivce from 5 days to 3 days and there is no data considered on the expenditure based on the days. So, a user may have preference in buying products only specific days due to various reasons like, 'a user may only prefer to buy during his week-off' or 'a user has preference in buying the groceries only during the a specific day of the week' etc. By estimating the classifiers without considering the data of the user expenditure specific to the days may not result in optimal results.

Reference - https://en.wikipedia.org/wiki/A/B_testing (https://en.wikipedia.org/wiki/A/B_testing)

Question 11

Additional structure is derived from originally unlabeled data when using clustering techniques. Since each customer has a ***customer segment*** it best identifies with (depending on the clustering algorithm applied), we can consider *'customer segment'* as an **engineered feature** for the data. Assume the wholesale distributor recently acquired ten new customers and each provided estimates for anticipated annual spending of each product category. Knowing these estimates, the wholesale distributor wants to classify each new customer to a ***customer segment*** to determine the most appropriate delivery service.

- How can the wholesale distributor label the new customers using only their estimated product spending and the **customer segment** data?

Hint: A supervised learner could be used to train on the original customers. What would be the target variable?

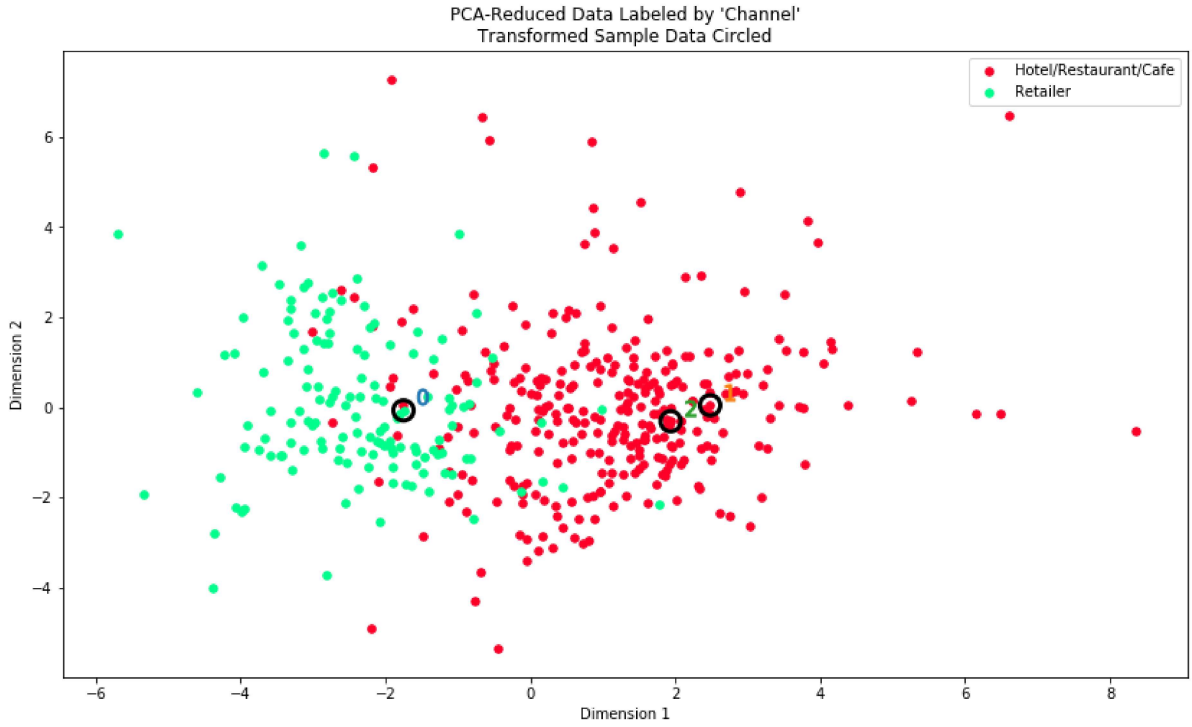
In this scenario, performing a supervised learning on the original customers with a target variable of customer segment should do the job. Since, the interest is in obtaining a customer segment from the given input data, we need to train the model using the input data to obtain or predict the customer segment.

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 to the original dataset.

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

In [19]:
```
# Display the clustering results based on 'Channel' data
vs.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?

- The number of clusters and the clustering algorithm choosen seems to compare the underlying distribution fairly well. A fair classification of this data would be to say on the basis of Fresh/Frozen and Milk/Grocery/Detergent papers. It is fair to say that Hotel/Restaurants/Cafe serve decent amount of Fresh/Frozen food as they needs serve fresh to the customers. So customers who tend to go these establishments tend to spend more on these categories. Where as in terms of Milk/Grocery/Detergent papers, customer usually buy these from retailers. Although it is not precise, the classification serves a good justification into these categories.
- Yes there could definitely be customer segments that could be classified purely by this distrubution. But, definitely not all of them.
- Yes, fairly consistent but not highly accurate as you can seem outliers visible in the 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.