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 DataFram
es

# 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?"
```

```
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	Del
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

1. Fresh Category is the most popular category.
2. Delicateseens it the least popular category amogst the size categories.

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 = [85, 181, 183]

# 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	16117	46197	92780	1026	40827	2944
1	112151	29627	18148	16745	4948	8550
2	36847	43950	20170	36534	239	47943

Question 1

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

Answer:
Customer 0 : Supermarket with fresh vegetable/ fruit sections also partially available.
Rationale : Buys a lot of grocery (92k) followed by milk(46K) and detergents(40K), but seems like almost doesn't buy frozen (1K) and delicatessen(3K).

Customer 1 : Markets or possible Greengrocer [1]
Rationale : Buys a lot of fresh products(112K) and milk(29K) and few of the grocery(18K), frozen(16K) and others. And often the focus propduct in the markets are fresh products.

Customer 2 : Delicatessen[1]
Rationale : Sells a lor of delicacies(fine food) (47K)

Ref 1: https://en.wikipedia.org/wiki/Grocery_store (https://en.wikipedia.org/wiki/Grocery_store)

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
import sklearn
from sklearn.tree import DecisionTreeRegressor
new_data = pd.DataFrame.copy(data)
new_data.drop(['Fresh'], axis = 1, inplace = True)
print(new_data.head())

# TODO: Split the data into training and testing sets using the removed featur
e as the target label
X_train, X_test, y_train, y_test = sklearn.cross_validation.train_test_split(n
ew_data, data['Fresh'], test_size = 0.25, random_state = 40)


# TODO: Create a decision tree regressor and fit it to the training set
regressor = DecisionTreeRegressor(random_state  = 2)
regressor.fit(X_train, y_train)
print(regressor)

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

```
   Milk  Grocery  Frozen  Detergents_Paper  Delicatessen
0  9656     7561     214              2674          1338
1  9810     9568    1762              3293          1776
2  8808     7684    2405              3516          7844
3  1196     4221    6404               507          1788
4  5410     7198    3915              1777          5185
DecisionTreeRegressor(criterion='mse', max_depth=None, max_features=None,
           max_leaf_nodes=None, min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, presort=False, random_state=2,
           splitter='best')
('Score of the prediction using the test set is', -0.50029244159308517)
```

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.

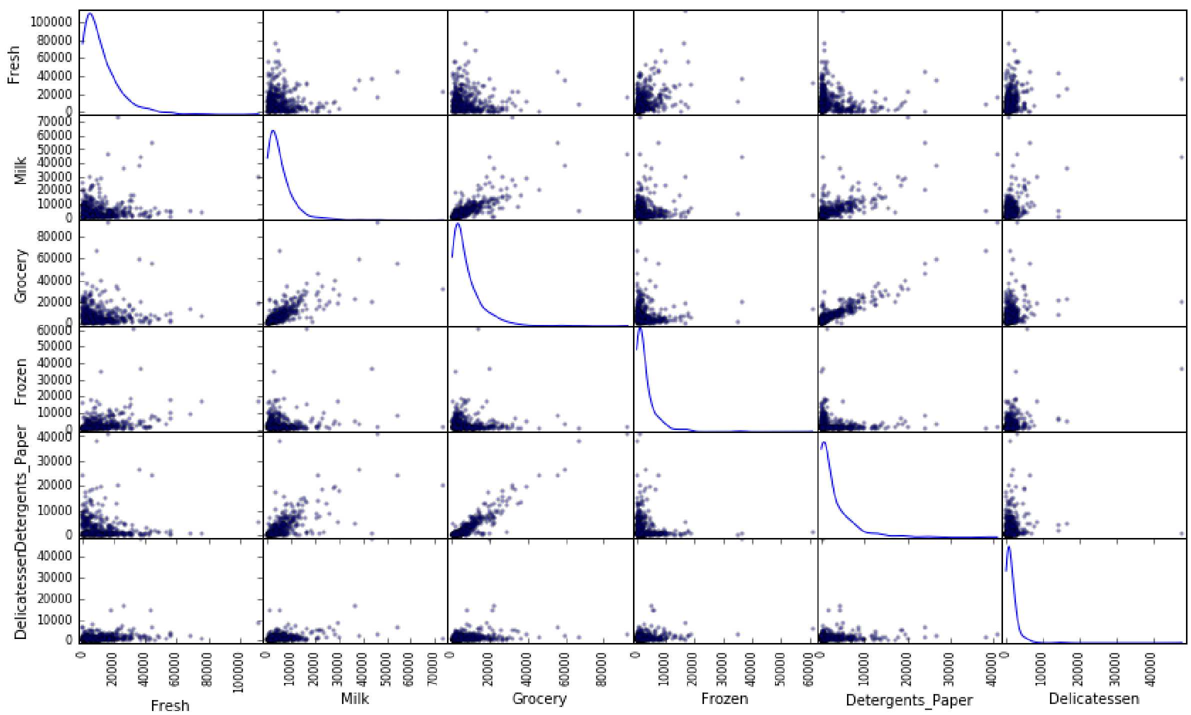
Answer:

1. Feature attempted to predict : Fresh
2. Reported Prediction Score : -0.5
3. Is the feature necessary for identifying customer's spending habit : Yes, as the model fails to fit the data i.e predict the feature (Fresh), when all the other features are available, this implies that the feature s necessary feature.

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 = (14,8), diagonal = 'kde');
```



Question 3

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

Answer: Yes, there are pair of features, that exhibit some degree of correlation i.e Milk vs Grocery, Milk vs Detergent_paper and grocery vs detergent_papers.
Yes, it does confirm our suspicions about the relevance of the feature we tried to predict. We predicted that the featues "Fresh" is independent and hence highly relevant, which we as observed in the scatter plots appears as so. There exists no concrete but rather random distribution when the dta was plotted against all the other features.
Highly skewed distribution of the data was observed. Almost all the features haver been observed as highly left skewed data distribution.

In [6]:
```
# Testing the correlated  features,  in the same earlier way
import sklearn
from sklearn.tree import DecisionTreeRegressor
new_data = pd.DataFrame.copy(data)
new_data.drop(['Milk'], axis = 1, inplace = True)
print(new_data.head() )
#print(data['Milk'].head())
#print(data.head())



# TODO: Split the data into training and testing sets using the removed featur
e as the target label
X_train, X_test, y_train, y_test = sklearn.cross_validation.train_test_split(n
ew_data, data['Milk'], test_size = 0.25, random_state = 40)

# TODO: Create a decision tree regressor and fit it to the training set
regressor = DecisionTreeRegressor(random_state  = 5, max_depth = 2)
regressor.fit(X_train, y_train)
#print(regressor)

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

```
   Fresh  Grocery  Frozen  Detergents_Paper  Delicatessen
0  12669     7561     214              2674          1338
1   7057     9568    1762              3293          1776
2   6353     7684    2405              3516          7844
3  13265     4221    6404               507          1788
4  22615     7198    3915              1777          5185
('Score of the prediction using the test set is', 0.28442881091521077)
```

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:

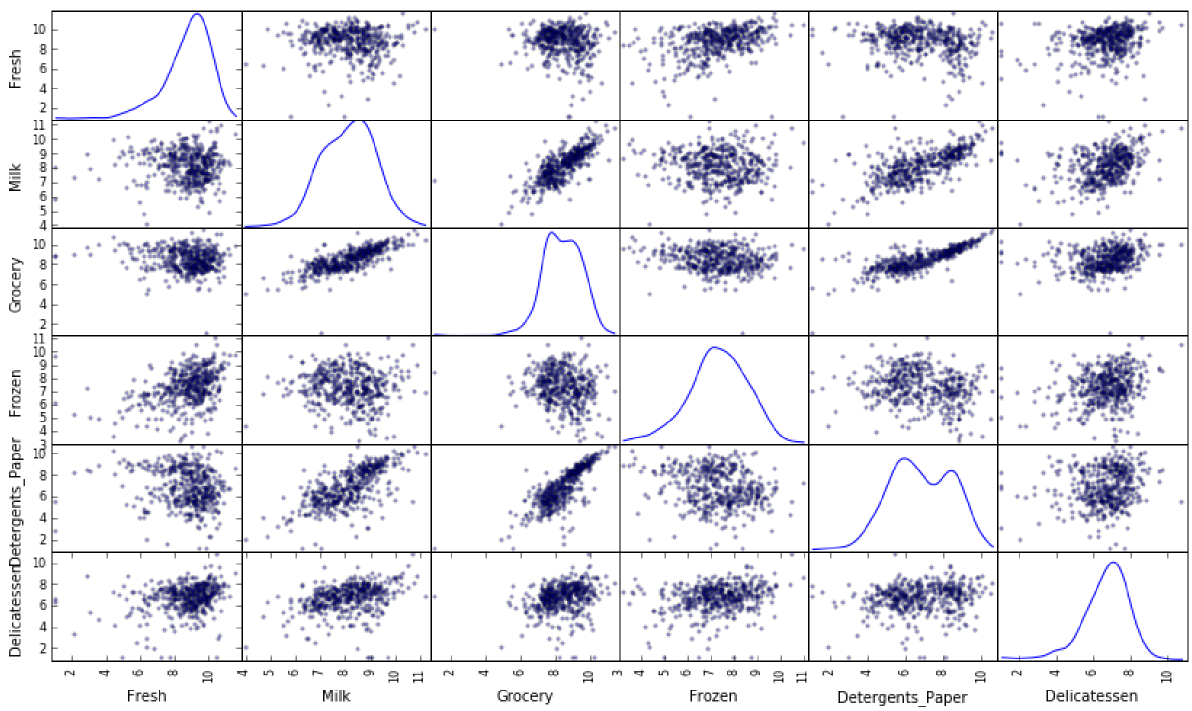
- Assign a copy of the data to `log_data` after applying a logarithm scaling. Use the `np.log` function for this.
- Assign a copy of the sample data to `log_samples` after applying a logrithm scaling. Again, use `np.log`.

In [85]:
```
# TODO: Scale the data using the natural logarithm
log_data = np.log( pd.DataFrame.copy(data))
#log_data.drop(['Milk'], axis = 1, inplace = True)
#print(log_data.head())

# TODO: Scale the sample data using the natural logarithm
#data.sample(n = 5,random_state = 1 )
log_samples = np.log(samples)
print('------------------------- Np log of the sample, data is')
print(log_samples)
print('------------------------- Np log of the whole dataset is')
print(log_data.loc[log_samples.index])

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

```
------------------------- Np log of the sample, data is
       Fresh       Milk    Grocery     Frozen  Detergents_Paper  Delicatessen
0   9.687630  10.740670  11.437986   6.933423         10.617099      7.987524
1  11.627601  10.296441   9.806316   9.725855          8.506739      9.053687
2  10.514529  10.690808   9.911952  10.505999          5.476464     10.777768
------------------------- Np log of the whole dataset is
      Fresh      Milk   Grocery    Frozen  Detergents_Paper  Delicatessen
0  9.446913  9.175335  8.930759  5.365976          7.891331      7.198931
1  8.861775  9.191158  9.166179  7.474205          8.099554      7.482119
2  8.756682  9.083416  8.946896  7.785305          8.165079      8.967504
```



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 [86]:
```
# Display the log-transformed sample data
display(log_samples)
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	9.687630	10.740670	11.437986	6.933423	10.617099	7.987524
1	11.627601	10.296441	9.806316	9.725855	8.506739	9.053687
2	10.514529	10.690808	9.911952	10.505999	5.476464	10.777768

Answer

1. Correlataion among the features identified earlier as being correlated still exists.
   Milk vs Grocery : Present (Stronger than before)
   Milk vs Detergent_paper : Present (Stronger than before)
   Grocery vs Detergent_papers : Present (Weaker than before)

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 [87]:
```
# 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)
    #print('Q1',Q1,'Q3',Q3,step)
    #display(log_data[feature].describe())

    # Display the outliers
    print "Data points considered outliers for the feature '{}' with Q1 : {} ,
 Q3 : {} :".format(feature,Q1,Q3)
    display(log_data[~((log_data[feature] >= Q1 - step) & (log_data[feature] <
= Q3 + step))])
    #outliers.extend(log_data[~((log_data[feature] >= Q1 - step) & (log_data[f
eature] <= Q3 + step))].index)
    #print('No of outlier to be removed, after considering the outlier for fea
ture ::(',features_considered_till_now ,') is ', len(outliers),' Outliers ar
e',outliers)

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

# Remove the outliers, if any were specified
print('Prior to outlier removal as identified for all features,  no of data po
int is ',len(log_data))
good_data = log_data.drop(log_data.index[outliers]).reset_index(drop = True)
print('After removal  of all outlier identified across all feature, no of data
 point is ',len(good_data))
```

Data points considered outliers for the feature 'Fresh' with Q1 : 8.04805870221 , Q3 : 9.73706394795 :

	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' with Q1 : 7.33498124004 , Q3 : 8.88048008859 :

	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' with Q1 : 7.67461620137 , Q3 : 9.27385367724 :

	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' with Q1 : 6.60967774917 , Q3 : 8.17589608318 :

	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' with Q1 :
5.54810142479 , Q3 : 8.27434059875 :
```

	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' with Q1 : 6.01
187465693 , Q3 : 7.50672842655 :
```

	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

```
('Prior to outlier removal as identified for all features,  no of data point
is ', 440)
('After removal  of all outlier identified across all feature, no of data poi
nt is ', 440)
```

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, there are more than one data points that are considered outliers for more tha one featuer for e.g data with index (154 => outlier for Milk, Grocery and Delicatessen, 75 => Grocery and Detergents_Paper, 65 => Grocery and Fresh e.t.c)
No, just because some category of products is bought more or less, does not imply that it is invalid data. Not sufficient business domain basis is present to support the claim. Furthermore, it seems valid as well e.g a Delicatessen or fine food shop is likely to buy a lot of fresh, delicatessen and very few grocery and detergetn_paper items.

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.

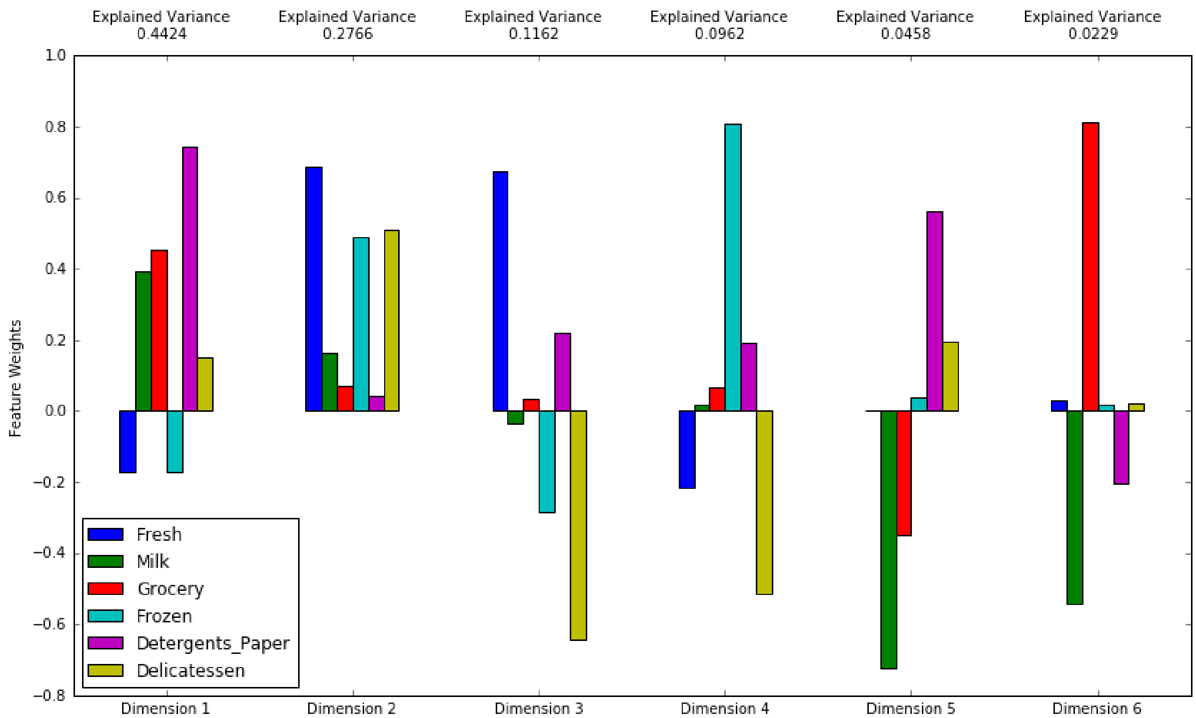
In the code block below, you will need to implement the following:

- 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 [88]:
```
# TODO: Apply PCA to the good data with the same number of dimensions as featu
res
from sklearn.decomposition import PCA
pca = PCA(n_components = 6)
pca.fit(good_data)
#print(pca.explained_variance_ratio_)

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

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



Question 5

*How much variance in the data is explained **in total** by the first and second principal component? What about the first four principal components? Using the visualization provided above, discuss what the first four dimensions best represent in terms of customer spending.*
Hint: A positive increase in a specific dimension corresponds with an *increase* of the *positive-weighted* features and a *decrease* of the *negative-weighted* features. The rate of increase or decrease is based on the indivdual feature weights.

Answer:
Total Variance explained by the 1st and 2nd principal component: 0.72
Total variance explained by the first 4 principal components : 0.9314

Qn : Using the visualization provided above, discuss what the first four dimensions best represent in terms of customer spending
Answer: First principal component Dimension : The dimension 1 represents the majority of the Customers spending in the Detergents_Paper followed by the Grocery, Milk and Delicatessen Category as (about 0.8,0.42,0.39 and 0.2) respectively. In addition ,on the contrary it represent the cusotmers negative spending in the Fresh and the Frozen category i.e (-0.2 and -0.2 respectively) i.e the fewer the customers spend on these two categories, the more this particular dimension represents them. Second PCA dimension : The dimension two represents the majority of the Customers spending in the Fresh, Delicatessen, Frozen on the majority basis(about 0.7, 0.53 and 0.5) respectively, hwile representing the customer's spending on Milk, Grocery and Detergents in minute scale i.e(0.2, 0.1 and 0.05 respectively). Third PCA dimension : This dimension represents the majority of the Customers Spending of Fresh category with mediocre representation of customer spending on Detergent and negligibly Grocery i.e (0.7,0.2 and 0.02 respectively). While in addition, on the contrary this dimension negatively relates with the customer's spending on Delicatessen on majority basis, Frozen on medium and Milk on negligible basis (i.e -0.7, -0.3,-0.1 respectively). Fourth PCA Dimension : This dimension represents the majority of the Customers Spending of Frozen category with mediocre representation of customer spending on Detergent and negligibly Grocery, Milk i.e (0.8,0.2 ,0.07 and 0.01 respectively). While in addition, on the contrary this dimension negatively relates with the customer's spending on Delicatessen on majority basis, and Fresh category on medium level (i.e -0.6 and -0.25 respectively).

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 [90]:
```
# Display sample log-data after having a PCA transformation applied
# log_samples1 = np.log(data.sample(n = 1,random_state = 1 ))
# pca_samples1 = pca.transform(log_samples1)
# #print(log_samples.index[0])
# print(log_samples1)
# display(log_samples1)
# display(pd.DataFrame(np.round(pca_samples1, 4), columns = pca_results.index.
values))

display(log_samples)
display(pd.DataFrame(np.round(pca_samples, 4), columns = pca_results.index.val
ues))
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	9.687630	10.740670	11.437986	6.933423	10.617099	7.987524
1	11.627601	10.296441	9.806316	9.725855	8.506739	9.053687
2	10.514529	10.690808	9.911952	10.505999	5.476464	10.777768

	Dimension 1	Dimension 2	Dimension 3	Dimension 4	Dimension 5	Dimension 6
0	5.3459	1.9442	0.7429	-0.2108	-0.5297	0.2928
1	2.1974	4.9048	0.0686	0.5623	-0.5195	-0.2369
2	0.4585	5.3459	-2.6856	-0.0173	-2.1850	0.2688

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 [92]:
```
# TODO: Fit PCA to the good data using only two dimensions
pca = PCA(n_components = 2)
pca.fit(good_data)

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

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

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

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 [93]:
```
# 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	5.3459	1.9442
1	2.1974	4.9048
2	0.4585	5.3459

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:
Advantages of using K- means :

1. General purpose algorithm.
2. K-means algorithm is very fast. [1]
3. Scales well to very large no of samples and applications in different fields [2]

Disadv :

1. Fails with local minima. It is hence useful, to restart it several times.
2. Sensitive to incorrect number of clusters, anisotropic distributed blobs, unequal variance[2]
3. Not good for uneven cluster size, and too many clusters

Advantage of using gaussian Mixture model clustering:

1. Can be thought of as genralising k-means that also incorporates information about the co-variance.[3]
2. Can learn Gaussian mixture models i.e (diagonal, spherical, tied and full covariance clustered data) [3]
3. Probabilistic model, that can cluster points along with their cluster inclusion probbility. [3]
4. Good for density estimated clustering

Disadvantage :

1. It is not scalable [4]

Choice of Algorithm :
Since in our "Feature scaling section", while observing the scatter plot, we do not observe complex shapes, spherical, diagonal or other complex patterns in the data when each features were compared across each other, following on the Occam's Razor principle and because k-means is fast and generic, we choose the simple generic k-means algorithm as the choice of algorithm for now.
PS : The gaussian modles has also been tried as practice session, however.

Ref :

1. http://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html (http://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html)
2. http://scikit-learn.org/stable/modules/clustering.html#k-means (http://scikit-learn.org/stable/modules/clustering.html#k-means)
3. http://scikit-learn.org/stable/modules/mixture.html (http://scikit-learn.org/stable/modules/mixture.html)
4. http://scikit-learn.org/stable/modules/clustering.html (http://scikit-learn.org/stable/modules/clustering.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.

Silhouette Score
The best value is 1 and the worst value is -1. Values near 0 indicate overlapping clusters. Negative values generally indicate that a sample has been assigned to the wrong cluster, as a different cluster is more similar. [1]
Ref:

1. http://scikit-learn.org/stable/modules/generated/sklearn.metrics.silhouette_score.html (http://scikit-learn.org/stable/modules/generated/sklearn.metrics.silhouette_score.html)

In [94]:
```
# TODO: Apply your clustering algorithm of choice to the reduced data -- try b
oth knn and gaussian
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

best_score = -1.0
best_cluster_size = 1
run_cluster_score_until_cluster_size = 15
for n_clusters in range(2,run_cluster_score_until_cluster_size):
    # for the last run, run the cluster with the best cluster size
    if n_clusters == run_cluster_score_until_cluster_size-1:
        n_clusters = best_cluster_size

    clusterer = KMeans(n_clusters = n_clusters).fit(reduced_data)

    # TODO: Predict the cluster for each data point
    preds = clusterer.predict(reduced_data)
    #print(preds)
    # 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 cluste
rs chosen
    score = silhouette_score(reduced_data,preds)
    print('No of CLuster ::',n_clusters,'score is ',score)
    if best_score < score:
        best_score        = score
        best_cluster_size = n_clusters
print('best cluster size is ::',best_cluster_size, ' Best cluster score is ::'
,best_score)
```

```
('No of CLuster ::', 2, 'score is ', 0.41971062030865836)
('No of CLuster ::', 3, 'score is ', 0.39597528613124733)
('No of CLuster ::', 4, 'score is ', 0.33288161925846227)
('No of CLuster ::', 5, 'score is ', 0.33970774658600555)
('No of CLuster ::', 6, 'score is ', 0.34763401188258558)
('No of CLuster ::', 7, 'score is ', 0.36085526675625107)
('No of CLuster ::', 8, 'score is ', 0.35562676057356912)
('No of CLuster ::', 9, 'score is ', 0.35897270243779089)
('No of CLuster ::', 10, 'score is ', 0.34875079134723336)
('No of CLuster ::', 11, 'score is ', 0.35032097868522694)
('No of CLuster ::', 12, 'score is ', 0.35851128013739708)
('No of CLuster ::', 13, 'score is ', 0.36498262848079643)
('No of CLuster ::', 2, 'score is ', 0.41916608320292309)
('best cluster size is ::', 2, ' Best cluster score is ::', 0.419710620308658
36)
```

In [76]:
```
# TODO: Apply gaussian mixture model gaussian
from sklearn import mixture
import numpy as np
from sklearn.metrics import silhouette_score

best_score = -1.0
best_cluster_size = 1
best_covariance_type = None
np.random.seed(1)
n_components_range = [2,3,4,5,6,7,8,9,10,11,None]
cv_types = ['spherical','tied','diag','full']

for cv_type in cv_types:
    for n_components in n_components_range:
        if cv_type == cv_types[-1]  and n_components == n_components_range[-1
]:
            print('best cluster size is ::',best_cluster_size, 'Best cv type i
s ',best_covariance_type,' Best cluster score is ::',best_score)
            n_components = best_cluster_size
            cv_type = best_covariance_type
        #elif cv_type != cv_types[-1] or (cv_type == cv_types[-1]  and n_compo
nents == n_components_range[-1]):
        if n_components != None:
            clusterer_gaus = mixture.GMM( n_components=n_components, covarianc
e_type=cv_type ).fit(reduced_data)
        #print(clusterer.means_)

            # TODO: Predict the cluster for each data point
            preds_gaus = clusterer_gaus.predict(reduced_data)
            #print(preds)
            # TODO: Find the cluster centers
            centers_gaus = clusterer_gaus.means_

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

            # TODO: Calculate the mean silhouette coefficient for the number o
f clusters chosen
            score = silhouette_score(reduced_data, preds)
            print('No of CLuster ::',n_components,' cv_type',cv_type,'score is
 ',score)
            if best_score < score:
                best_score        = score
                best_cluster_size = n_components
                best_covariance_type = cv_type

print('Final best cluster size is ::',best_cluster_size, 'Best cv type is ',be
st_covariance_type,' Best cluster score is ::',best_score)
```

```
('No of CLuster ::', 2, ' cv_type', 'spherical', 'score is ', 0.4191660832029
232)
('No of CLuster ::', 3, ' cv_type', 'spherical', 'score is ', 0.4191660832029
232)
('No of CLuster ::', 4, ' cv_type', 'spherical', 'score is ', 0.4191660832029
232)
('No of CLuster ::', 5, ' cv_type', 'spherical', 'score is ', 0.4191660832029
232)
('No of CLuster ::', 6, ' cv_type', 'spherical', 'score is ', 0.4191660832029
232)
('No of CLuster ::', 7, ' cv_type', 'spherical', 'score is ', 0.4191660832029
232)
('No of CLuster ::', 8, ' cv_type', 'spherical', 'score is ', 0.4191660832029
232)
('No of CLuster ::', 9, ' cv_type', 'spherical', 'score is ', 0.4191660832029
232)
('No of CLuster ::', 10, ' cv_type', 'spherical', 'score is ', 0.419166083202
9232)
('No of CLuster ::', 11, ' cv_type', 'spherical', 'score is ', 0.419166083202
9232)
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('No of CLuster ::', 3, ' cv_type', 'tied', 'score is ', 0.4191660832029232)
('No of CLuster ::', 4, ' cv_type', 'tied', 'score is ', 0.4191660832029232)
('No of CLuster ::', 5, ' cv_type', 'tied', 'score is ', 0.4191660832029232)
('No of CLuster ::', 6, ' cv_type', 'tied', 'score is ', 0.4191660832029232)
('No of CLuster ::', 7, ' cv_type', 'tied', 'score is ', 0.4191660832029232)
('No of CLuster ::', 8, ' cv_type', 'tied', 'score is ', 0.4191660832029232)
('No of CLuster ::', 9, ' cv_type', 'tied', 'score is ', 0.4191660832029232)
('No of CLuster ::', 10, ' cv_type', 'tied', 'score is ', 0.4191660832029232)
('No of CLuster ::', 11, ' cv_type', 'tied', 'score is ', 0.4191660832029232)
('No of CLuster ::', 2, ' cv_type', 'diag', 'score is ', 0.4191660832029232)
('No of CLuster ::', 3, ' cv_type', 'diag', 'score is ', 0.4191660832029232)
('No of CLuster ::', 4, ' cv_type', 'diag', 'score is ', 0.4191660832029232)
('No of CLuster ::', 5, ' cv_type', 'diag', 'score is ', 0.4191660832029232)
('No of CLuster ::', 6, ' cv_type', 'diag', 'score is ', 0.4191660832029232)
('No of CLuster ::', 7, ' cv_type', 'diag', 'score is ', 0.4191660832029232)
('No of CLuster ::', 8, ' cv_type', 'diag', 'score is ', 0.4191660832029232)
('No of CLuster ::', 9, ' cv_type', 'diag', 'score is ', 0.4191660832029232)
('No of CLuster ::', 10, ' cv_type', 'diag', 'score is ', 0.4191660832029232)
('No of CLuster ::', 11, ' cv_type', 'diag', 'score is ', 0.4191660832029232)
('No of CLuster ::', 2, ' cv_type', 'full', 'score is ', 0.4191660832029232)
('No of CLuster ::', 3, ' cv_type', 'full', 'score is ', 0.4191660832029232)
('No of CLuster ::', 4, ' cv_type', 'full', 'score is ', 0.4191660832029232)
('No of CLuster ::', 5, ' cv_type', 'full', 'score is ', 0.4191660832029232)
('No of CLuster ::', 6, ' cv_type', 'full', 'score is ', 0.4191660832029232)
('No of CLuster ::', 7, ' cv_type', 'full', 'score is ', 0.4191660832029232)
('No of CLuster ::', 8, ' cv_type', 'full', 'score is ', 0.4191660832029232)
('No of CLuster ::', 9, ' cv_type', 'full', 'score is ', 0.4191660832029232)
('No of CLuster ::', 10, ' cv_type', 'full', 'score is ', 0.4191660832029232)
('No of CLuster ::', 11, ' cv_type', 'full', 'score is ', 0.4191660832029232)
('best cluster size is ::', 2, 'Best cv type is ', 'spherical', ' Best cluste
r score is ::', 0.4191660832029232)
('No of CLuster ::', 2, ' cv_type', 'spherical', 'score is ', 0.4191660832029
232)
('Final best cluster size is ::', 2, 'Best cv type is ', 'spherical', ' Best
cluster score is ::', 0.4191660832029232)
```

Question 7

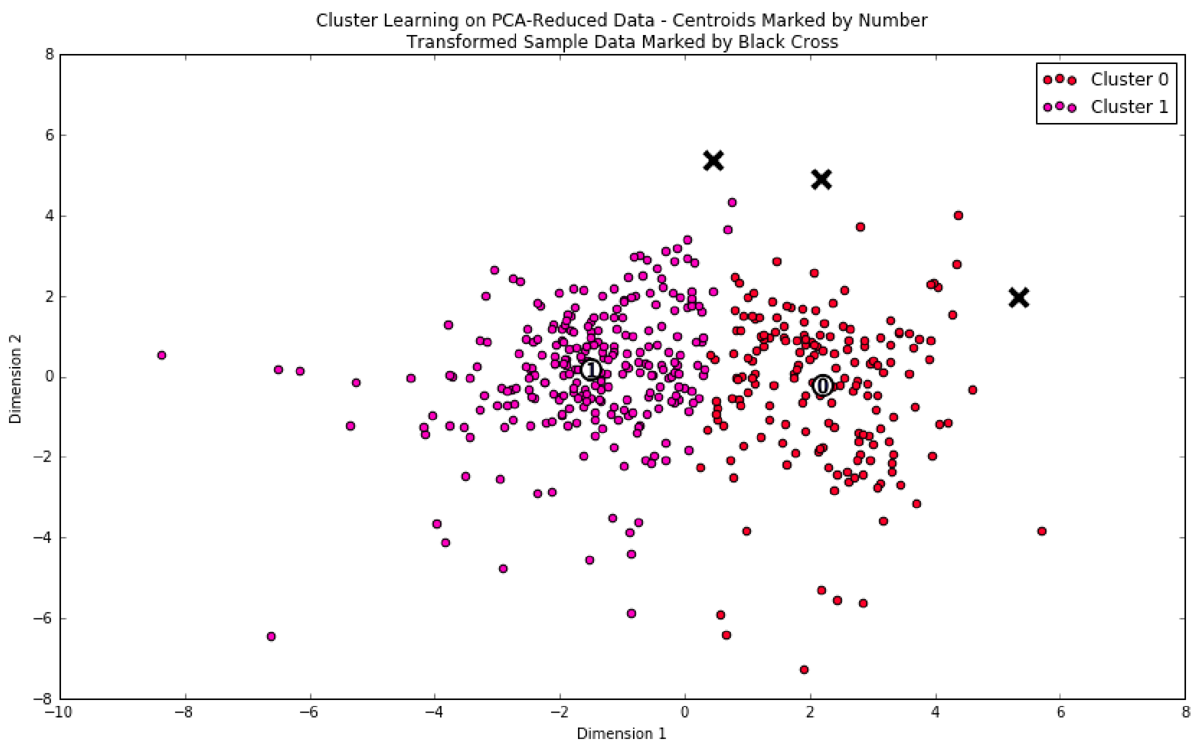
Report the silhouette score for several cluster numbers you tried. Of these, which number of clusters has the best silhouette score?

Answer: For the scores of several clusters tried, see the score in the earlier code run.
Best silhoutte score is 0.419 for 2 clusters (K-means).

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 [95]:
```
# 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 [98]:
```
# 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	3570	7749	12463	900	4567	966
Segment 1	8994	1909	2366	2081	290	681

In [99]:
```
display(samples)
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	16117	46197	92780	1026	40827	2944
1	112151	29627	18148	16745	4948	8550
2	36847	43950	20170	36534	239	47943

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:
Sgement 0 Customer Cluster : Most likely "Super Markets", as they tend to buy a lot of grocery, milk and detergents.

Sgement 1 Customer Cluster : Most likely "Green Gorcers or Farmers market", as they tend to buy a lot of fresh category products with minial purchase of other category products.

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 [100]:
```
# 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:
Prediction is consistent with Customer 0's charactersics, as highest grocery sales is consistent with the customer's portfolio, followed by Milk, Fresh and Detergent papers respectively. Also the lowest amount of purchase of the frozen and the delicatessen category for cluster 0 is in consistence with the customer 0.

Prediction for customer 1 is inconsistent with the cluster 0. The highest amount of purchase of the fresh category is in consistent more with the cluster segment 1. Hower it being classified as the cluster segment 0 is bit difficult to explain.

Prediction for customer 2 as belonging to cluster segment 1 is consistent with cluster 2. Cluster 2 represents a cluster which buys a lot less of Grocery but other products, which can also be seen in the Customer Sample 2

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:
It is hihgly likely that the delivery service time from 3 days to 5 days is likely to affect the customers in different way. The first cluster of customers tends to buy the grocery more, which being the non-perishable good, is more likely to not suffer from the delayed delivery. However, in case of the cluster 2 i.e who buys the fresh foods i.e perishable goods in the large quantity the delay would likely mean, an impossible business as they cannot sell the perished goods to the customers. Hence for the customers in cluster 2, it might be more reasonable to decrease the customers delivery time from three days down to small time intervals. The company should most likely test the delayed delivery trials on the first group of customers, on the first basis. If the trial is a sucess then only they should go down testing to group 2, which is the more riskier group. Direct feedback or the customer survey for such groups may even be desiredd for the second groupd prior to conducting the trial on the second group, if they are concerned about the customer loss. For both the case, the customer with lower purchase amount i.e lower value order customers form each cluster may be desirable to test with.

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?

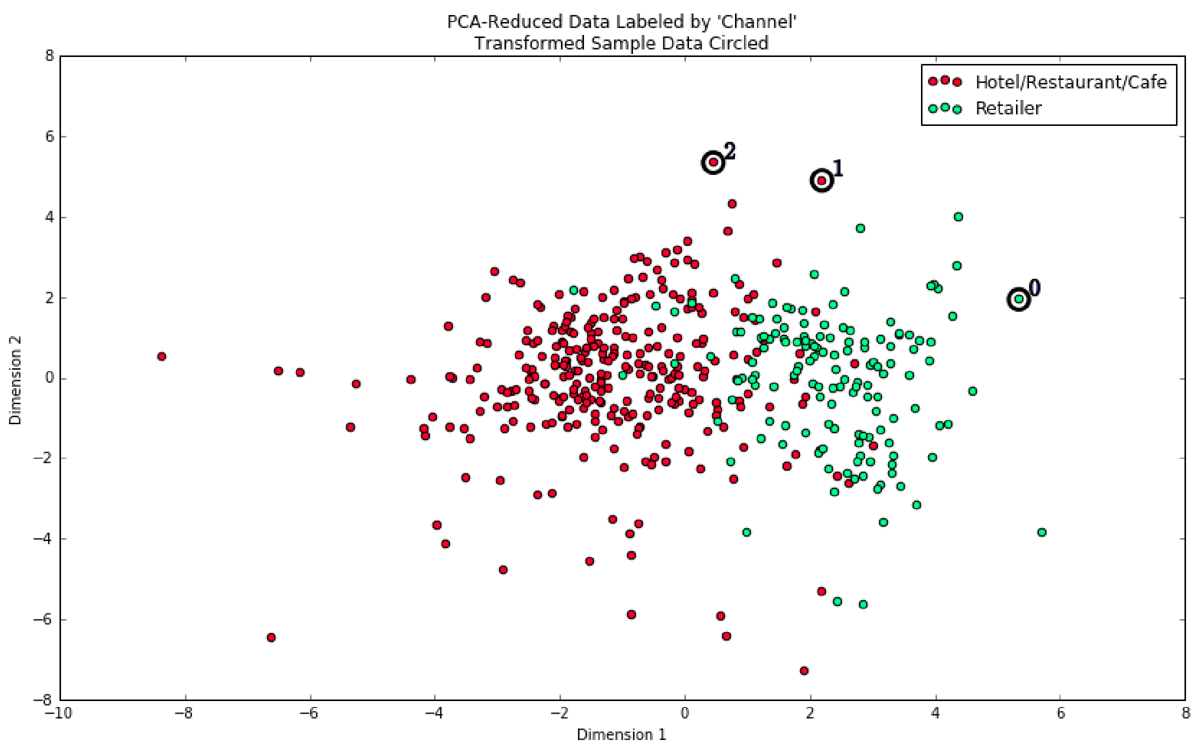
Answer:
Purchase weekday could also be one of the other relevant product feature that we will like to include, to further cluster customers including the weekday they prefer to buy in consideration.

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 [101]:
```
# 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 clsutering algorithm(k-means) and number of cluster(2) we' have choosen fits perfectly to the underlying distribution, considerig the fact that the distribution is well represented as two clusters with the retailers clustered along the right side, while the hotel/ restaurant/ cafe are represented along the left cluster in the diagram we plotted above, which is in consistence with the cluster obtained from the algorrithm.
These classifications seem to be however inconsistent with our previous defination of the customer segments, the human reasoning bias seems to have come into effect, and we were unable to classify the hotels/ restaurant/ cafes as exactly as such and mistakenly classified it as green grocer's and farmer's market, which now taking into hotels into perspective seems more reasoned choice , as the customers tended to buy a lot grocery along with the fresh foods as well. The lack of business domain knowledge as to the type of customers that were involved with the company seems to have limited our analysis to incorrect conclusion in this particular case.

> **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.