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() f
or DataFrames

# Show matplotlib plots inline (nicely formatted in the notebook)
%matplotlib inline

# Load the wholesale customers dataset
try:
    data = pd.read_csv("customers.csv")
    data.drop(['Region', 'Channel'], axis = 1, inplace = True)
    print "Wholesale customers dataset has {} samples with {} featu
res each.".format(*data.shape)
except:
    print "Dataset could not be loaded. Is the dataset missing?"
```

```
/Applications/anaconda/lib/python2.7/site-packages/matplotlib/font
_manager.py:273: UserWarning: Matplotlib is building the font cach
e using fc-list. This may take a moment.
  warnings.warn('Matplotlib is building the font cache using fc-li
st. This may take a moment.')
```

```
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())
display(data)
```

	Fresh	Milk	Grocery	Frozen	Detergents_Pap
count	440.000000	440.000000	440.000000	440.000000	440.000000
mean	12000.297727	5796.265909	7951.277273	3071.931818	2881.493182
std	12647.328865	7380.377175	9503.162829	4854.673333	4767.854448
min	3.000000	55.000000	3.000000	25.000000	3.000000
25%	3127.750000	1533.000000	2153.000000	742.250000	256.750000
50%	8504.000000	3627.000000	4755.500000	1526.000000	816.500000
75%	16933.750000	7190.250000	10655.750000	3554.250000	3922.000000
max	112151.000000	73498.000000	92780.000000	60869.000000	40827.000000

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	12669	9656	7561	214	2674	1338
1	7057	9810	9568	1762	3293	1776
2	6353	8808	7684	2405	3516	7844
3	13265	1196	4221	6404	507	1788
4	22615	5410	7198	3915	1777	5185
5	9413	8259	5126	666	1795	1451
6	12126	3199	6975	480	3140	545
7	7579	4956	9426	1669	3321	2566
8	5963	3648	6192	425	1716	750
9	6006	11093	18881	1159	7425	2098

10	3366	5403	12974	4400	5977	1744
11	13146	1124	4523	1420	549	497
12	31714	12319	11757	287	3881	2931
13	21217	6208	14982	3095	6707	602
14	24653	9465	12091	294	5058	2168
15	10253	1114	3821	397	964	412
16	1020	8816	12121	134	4508	1080
17	5876	6157	2933	839	370	4478
18	18601	6327	10099	2205	2767	3181
19	7780	2495	9464	669	2518	501
20	17546	4519	4602	1066	2259	2124
21	5567	871	2010	3383	375	569
22	31276	1917	4469	9408	2381	4334
23	26373	36423	22019	5154	4337	16523
24	22647	9776	13792	2915	4482	5778
25	16165	4230	7595	201	4003	57
26	9898	961	2861	3151	242	833
27	14276	803	3045	485	100	518
28	4113	20484	25957	1158	8604	5206
29	43088	2100	2609	1200	1107	823
...	...	...	...	...	...	...
410	6633	2096	4563	1389	1860	1892
411	2126	3289	3281	1535	235	4365
412	97	3605	12400	98	2970	62
413	4983	4859	6633	17866	912	2435
414	5969	1990	3417	5679	1135	290
415	7842	6046	8552	1691	3540	1874
416	4389	10940	10908	848	6728	993
417	5065	5499	11055	364	3485	1063
418	660	8494	18622	133	6740	776
419	8861	3783	2223	633	1580	1521

420	4456	5266	13227	25	6818	1393
421	17063	4847	9053	1031	3415	1784
422	26400	1377	4172	830	948	1218
423	17565	3686	4657	1059	1803	668
424	16980	2884	12232	874	3213	249
425	11243	2408	2593	15348	108	1886
426	13134	9347	14316	3141	5079	1894
427	31012	16687	5429	15082	439	1163
428	3047	5970	4910	2198	850	317
429	8607	1750	3580	47	84	2501
430	3097	4230	16483	575	241	2080
431	8533	5506	5160	13486	1377	1498
432	21117	1162	4754	269	1328	395
433	1982	3218	1493	1541	356	1449
434	16731	3922	7994	688	2371	838
435	29703	12051	16027	13135	182	2204
436	39228	1431	764	4510	93	2346
437	14531	15488	30243	437	14841	1867
438	10290	1981	2232	1038	168	2125
439	2787	1698	2510	65	477	52

440 rows × 6 columns

Implementation: Selecting Samples

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

In [3]:
```
# TODO: Select three indices of your choice you wish to sample from the dataset
indices = [1,100,200]

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

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

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	7057	9810	9568	1762	3293	1776
1	11594	7779	12144	3252	8035	3029
2	3067	13240	23127	3941	9959	731

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.

0: typical grocery customer buying food fresh and milk (low income) 1: could be upper middle class family shopping in supermarket and spendind a lot on fresh products and delicatessen 2: buyer living near the grocery who is buying milk and some staff nearby

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]:
```
from sklearn.cross_validation import train_test_split
from sklearn import tree
# TODO: Make a copy of the DataFrame, using the 'drop' function to drop the given feature
new_data = data.drop(['Delicatessen'],axis=1, inplace = False)
# TODO: Split the data into training and testing sets using the given feature as the target
X=new_data
y=data['Delicatessen']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)

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

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

```
-1.7111306747
```

Question 2

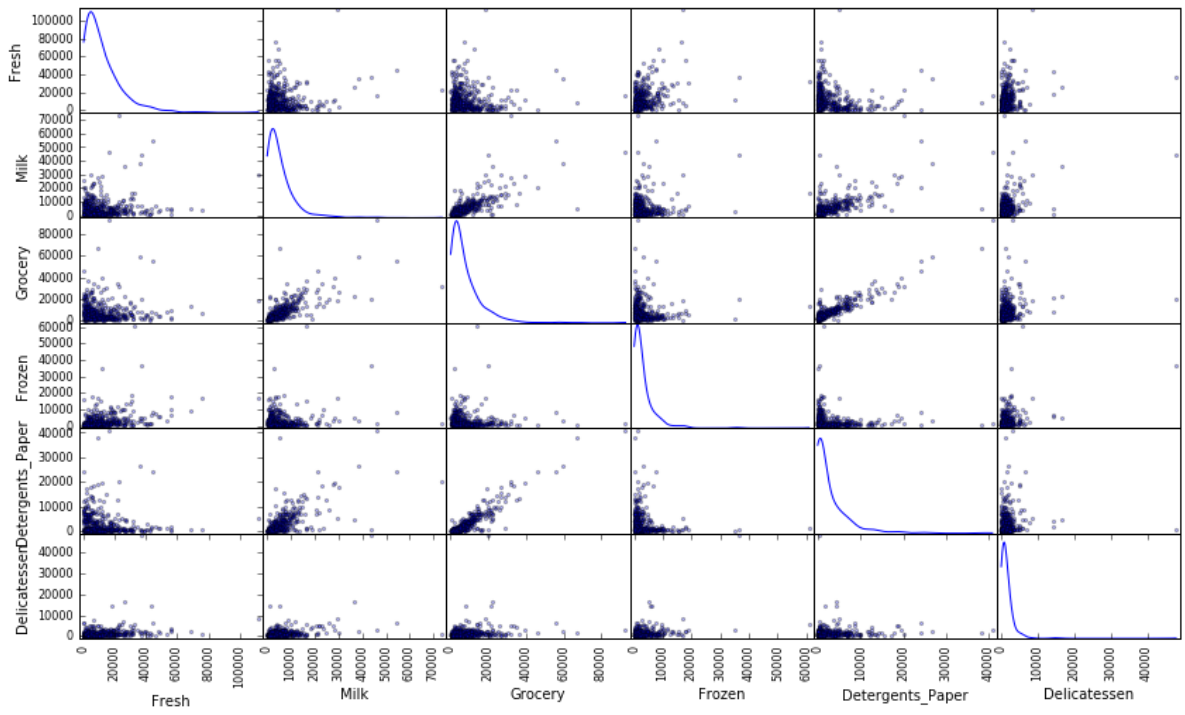
Which feature did you attempt to predict? What was the reported prediction score? Is this feature relevant for identifying a specific customer?
Hint: The coefficient of determination, `R^2`, is scored between 0 and 1, with 1 being a perfect fit. A negative `R^2` implies the model fails to fit the data.

I've tried to predict feature 'Delicatessen', but score was negative -1.7111306747; which mean that model fails to predict.

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?

There is clear correlation between milk and grocery. Delicatessen (feature I've tried to predict) looks like independent. It converm relevance of 'Delicatessen' in identifing the customer. Data for featurs are distribute log normally. Most data points lie near mean of the log normal distribution.

Data Preprocessing

In this section, you will preprocess the data to create a better representation of customers by performing a scaling on the data and detecting (and optionally removing) outliers. Preprocessing data is often times a critical step in assuring that results you obtain from your analysis are significant and meaningful.

Implementation: Feature Scaling

If data is not normally distributed, especially if the mean and median vary significantly (indicating a large skew), it is most often appropriate (http://econbrowser.com/archives/2014/02/use-of-logarithms-in-economics) to apply a non-linear scaling — particularly for financial data. One way to achieve this scaling is by using a Box-Cox test (http://scipy.github.io/devdocs/generated/scipy.stats.boxcox.html), which calculates the best power transformation of the data that reduces skewness. A simpler approach which can work in most cases would be applying the natural logarithm.

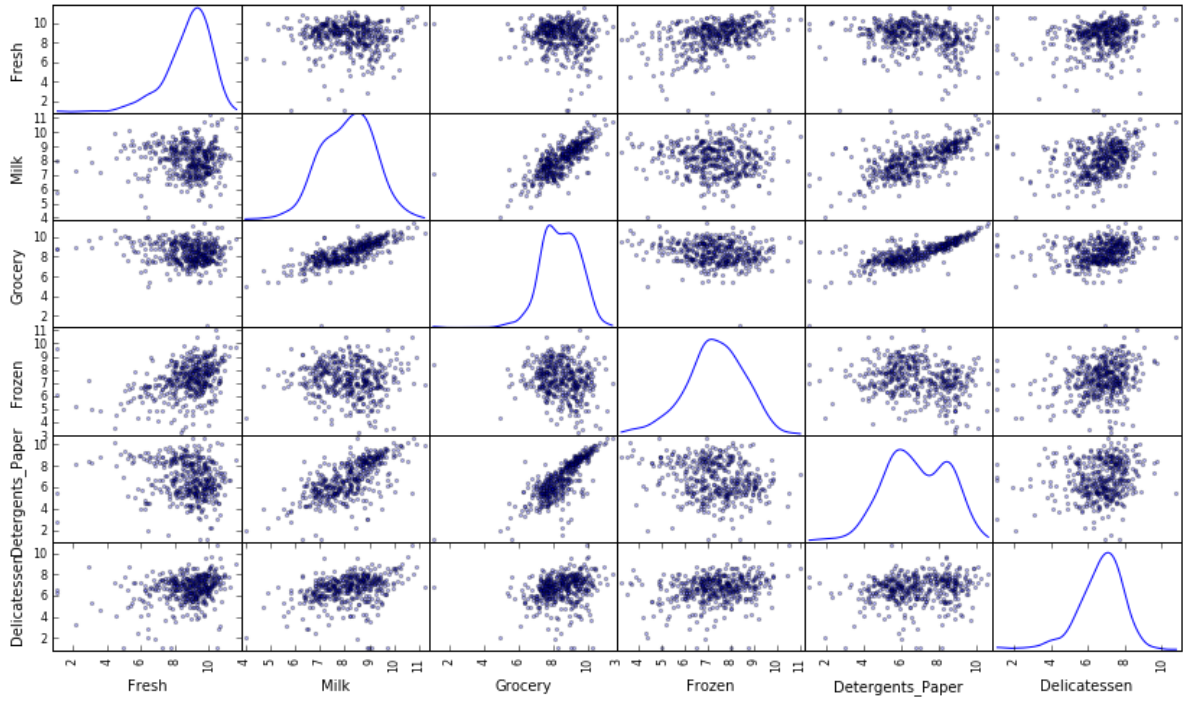
In the code block below, you will need to implement the following:

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

In [6]:
```
import numpy as np
# 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 featu
res
pd.scatter_matrix(log_data, alpha = 0.3, figsize = (14,8), diagonal
= 'kde');
```



Observation

After applying a natural logarithm scaling to the data, the distribution of each feature should appear much more normal. For any pairs of features you may have identified earlier as being correlated, observe here whether that correlation is still present (and whether it is now stronger or weaker than before).

Run the code below to see how the sample data has changed after having the natural logarithm applied to it.

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

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	8.861775	9.191158	9.166179	7.474205	8.099554	7.482119
1	9.358243	8.959183	9.404590	8.087025	8.991562	8.015988
2	8.028455	9.490998	10.048756	8.279190	9.206232	6.594413

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 [13]:
```
import numpy as np
# For each feature find the data points with extreme high or low va
lues
for feature in log_data.keys():

    # TODO: Calculate Q1 (25th percentile of the data) for the give
n feature
    Q1 = np.percentile(log_data[feature],25)

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

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

    # Display the outliers
    print "Data points considered outliers for the feature '{}':".f
ormat(feature)
    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  = [65,66,154,75,128]

# Remove the outliers, if any were specified
good_data = log_data.drop(log_data.index[outliers]).reset_index(dro
p = 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? Should these data points be removed from the dataset? If any data points were added to the `outliers` list to be removed, explain why.

Yes, the following points are outliers in more then 1 category: 65,66,154,75,128. All those outliers in more then 1 category have been removed.

Feature Transformation

In this section you will use principal component analysis (PCA) to draw conclusions about the underlying structure of the wholesale customer data. Since using PCA on a dataset calculates the dimensions which best maximize variance, we will find which compound combinations of features best describe customers.

Implementation: PCA

Now that the data has been scaled to a more normal distribution and has had any necessary outliers removed, we can now apply PCA to the `good_data` to discover which dimensions about the data best maximize the variance of features involved. In addition to finding these dimensions, PCA will also report the *explained variance ratio* of each dimension — how much variance within the data is explained by that dimension alone.

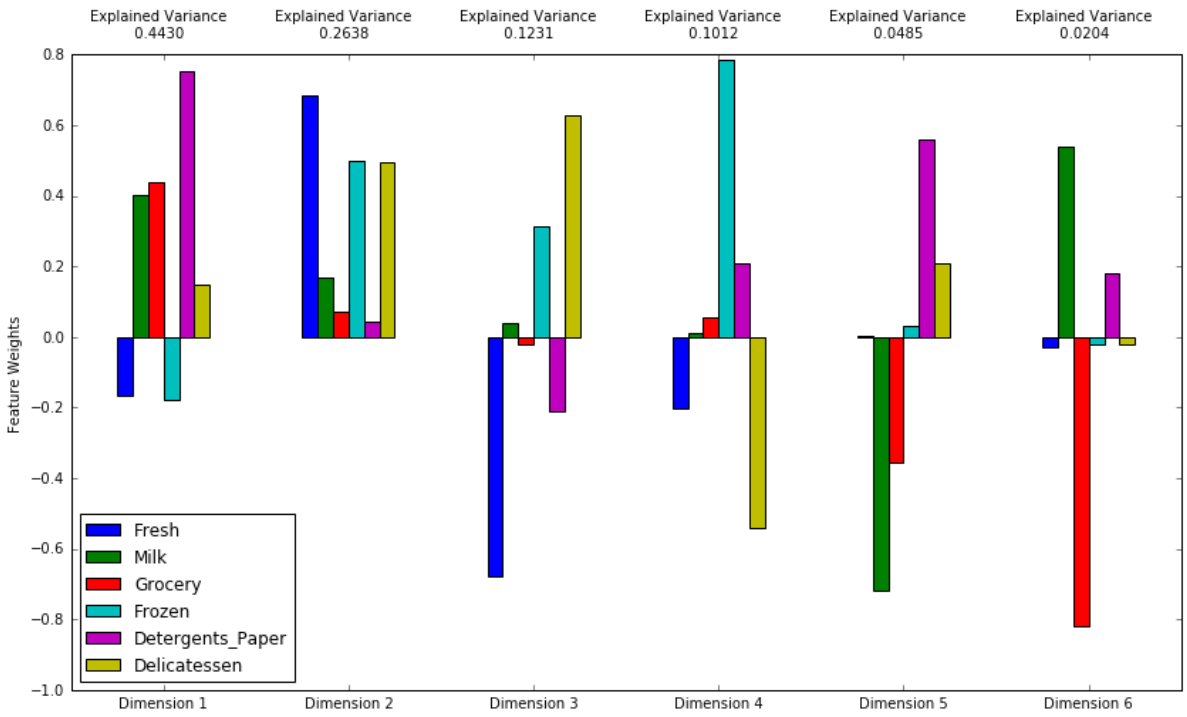
In the code block below, you will need to implement the following:

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

In [14]:
```
from sklearn.decomposition import PCA
# TODO: Apply PCA to the good data with the same number of dimensions as features
pca = PCA(n_components=6)
pca.fit(good_data)

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

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



Question 5

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

1st and 2nd PCA explain 0.7068 total variance. First four PCA explain 0.9311 of total variance. 1st PCA is best represents typical customer spending (milk+grocery+detergent_paper) without fresh or frozen. Dimension 2 corresponding to the gourmet customer: fresh, frozen and delicatessen. Dimensions 3 with prevailing fresh and no delicatessen could be vegan menu and dimension 4 is frozen-lower low income person.

Observation

Run the code below to see how the log-transformed sample data has changed after having a PCA transformation applied to it in six dimensions. Observe the numerical value for the first four dimensions of the sample points. Consider if this is consistent with your initial interpretation of the sample points.

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

	Dimension 1	Dimension 2	Dimension 3	Dimension 4	Dimension 5	Dimension 6
0	1.7887	0.8123	0.2315	-0.0036	-0.1194	0.2106
1	2.3579	1.7393	0.2210	0.2840	0.5939	0.0148
2	2.9903	0.3645	0.2521	1.5653	-0.1922	-0.1244

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 [16]:
```
from sklearn.decomposition import PCA
# 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 [17]:
```
# Display sample log-data after applying PCA transformation in two dimensions
display(pd.DataFrame(np.round(pca_samples, 4), columns = ['Dimension 1', 'Dimension 2']))
```

	Dimension 1	Dimension 2
0	1.7887	0.8123
1	2.3579	1.7393
2	2.9903	0.3645

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?

```
K-Means is one of the simplest clustering algorithm with very-large sca
lability. Algorithm assumes the number of clusters fixed apriory and mi
nimized objective function defined as sum of squared distance among dat
a points and cluster centers. So it is fast, robust and easy to underst
and algorithm. Computational time: O(tknd), where n is N  objects, k is
N clusters, d is N dimension of each object, and t  is N iterations. No
rmally, k, t, d << n. Apriory specification of the number of clusters a
nd centers. Algorithm is not handling well outliers and non-linear data
sets.
```

More details: https://sites.google.com/site/dataclusteringalgorithms/k-means-clustering-algorithm (https://sites.google.com/site/dataclusteringalgorithms/k-means-clustering-algorithm)

```
A Gaussian mixture model is a probabilistic model that assumes all the
data points are generated from a mixture of a finite number of Gaussian
distributions with unknown parameters. Gaussian mixture algorithms assu
mes than all initial data gas been generated by Gaussian distribution w
ith unknown parametrs. Expectation-maximization algorithm of GMM has th
e following pros and cons:
```

Advantages: 1) It is the fastest algorithm for learning mixture models. 2) As this algorithm maximizes only the likelihood, it will not bias the means towards zero, or bias the cluster sizes to have specific structures that might or might not apply. Disadvantages: 1) When one has insufficiently many points per mixture, estimating the covariance matrices becomes difficult, and the algorithm is known to diverge and find solutions with infinite likelihood unless one regularizes the covariances artificially. 2) This algorithm will always use all the components it has access to, needing held-out data or information theoretical criteria to decide how many components to use in the absence of external cues. More details: http://scikit-learn.org/stable/modules/mixture.html#pros-and-cons-of-class-gmm-expectation-maximization-inference (http://scikit-learn.org/stable/modules/mixture.html#pros-and-cons-of-class-gmm-expectation-maximization-inference)

```
After normaization of the data and removal of outliers, initial data di
stribution are close to the Gaussian distributions. So it mean, that Ga
ussian Mixture Model could be applied for clustering on wholesale custi
mer prepared data.
```

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 [24]:
```
from sklearn import mixture
from sklearn import metrics
# TODO: Apply your clustering algorithm of choice to the reduced da
ta
number_of_clusters=2
clusterer = mixture.GMM(n_components=number_of_clusters)
clusterer.fit(reduced_data)

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

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

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

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

```
[[ 1.63707508 -0.17862565]
 [-1.30917139  0.1428472 ]]
0.411818864386
```

Question 7

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

2 clusters score=0.411818864386 3 clusters score=0.373560747175 4 clusters score=0.309764770906 The best silhouette score for 2 clusters. Without removal of outliers it would be best silhouette score for 3 clusters. So preparation of data set is extremely important!

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 [25]:
```
# 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 [26]:
```
# 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	4316	6347	9555	1036	3046	945
Segment 1	8812	2052	2689	2058	337	712

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'`.

Segment 0 could represent typical grocery establishments. Segment 1 could represents fresh and frozen lover.

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 [27]:
```
# Display the predictions
for i, pred in enumerate(sample_preds):
    print "Sample point", i, "predicted to be in Cluster", pred
```

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

Initially I guess 0 sample point-segment 0, 1 sample point - segment 1 and 1 sample point-segment 1. All sample points lies in the Cluster 0 and surprisingly represents Segment 0.

Conclusion

Question 10

Companies often run A/B tests (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?

The controlling parameter for A/B test will be delivery service: it changes from 5 days to 3 days a week. For example, my testing hyphotesis could be: 1) Cluster 0 sample customer spendings will decrease 2) Cluster 0 sample customer spendings will decrease. So knowing the structure of the data (2 clusters), allow me to formulate hyphotesis for cluster 0 only. Based on the results of the sample customer from Cluster 0, I can conclude about the whole Cluster 0 behaviour (assuming I've picked representative or average sample customer from Cluster 0).

Question 11

Assume the wholesale distributor wanted to predict some other feature for each customer based on the purchasing information available. How could the wholesale distributor use the structure of the data to assist a supervised learning analysis?

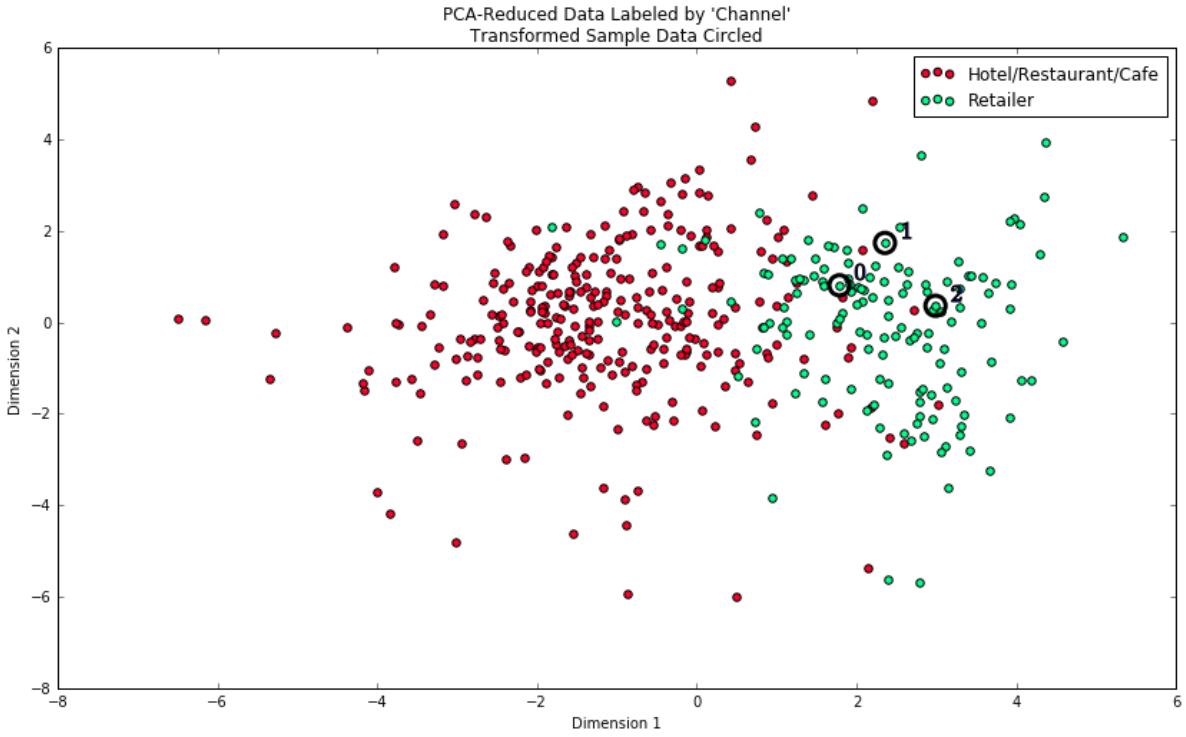
2 main customer segments could be used as customer types for the supervised learning analysis. So the whosale distributor could have a close look on each of behaviour patterns of those 2 customer segments and assumes that this behaviour pattern is valid for each customer from the segment.

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 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 [28]:
```
# 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?

Clustering algorithm have splitted sutomers well between HoReCa (Segment 1) and Retail (Segment 0) classes. There are no pure Retail or HoReCa customers. My previous classification of customers were based mainly on the customer preferences and is not consistent with answer.

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.