customer_segments

April 11, 2018

1 Machine Learning Engineer Nanodegree

1.1 Unsupervised Learning

1.2 Project: Creating Customer Segments

Welcome to the third project of the Machine Learning Engineer Nanodegree! In this notebook, some template code has already been provided for you, and it will be your job to implement the additional functionality necessary to successfully complete this project. Sections that begin with **'Implementation'** in the header indicate that the following block of code will require additional functionality which you must provide. Instructions will be provided for each section and the specifics of the implementation are marked in the code block with a `'TODO'` statement. Please be sure to read the instructions carefully!

In addition to implementing code, there will be questions that you must answer which relate to the project and your implementation. Each section where you will answer a question is preceded by a **'Question X'** header. Carefully read each question and provide thorough answers in the following text boxes that begin with **'Answer:'**. Your project submission will be evaluated based on your answers to each of the questions and the implementation you provide.

> **Note:** Code and Markdown cells can be executed using the **Shift + Enter** keyboard shortcut. In addition, Markdown cells can be edited by typically double-clicking the cell to enter edit mode.

1.3 Getting Started

In this project, you will analyze a dataset containing data on various customers' annual spending amounts (reported in *monetary units*) of diverse product categories for internal structure. One goal of this project is to best describe the variation in the different types of customers that a wholesale distributor interacts with. Doing so would equip the distributor with insight into how to best structure their delivery service to meet the needs of each customer.

The dataset for this project can be found on the UCI Machine Learning Repository. For the purposes of this project, the features `'Channel'` and `'Region'` will be excluded in the analysis — with focus instead on the six product categories recorded for customers.

Run the code block below to load the wholesale customers dataset, along with a few of the necessary Python libraries required for this project. You will know the dataset loaded successfully if the size of the dataset is reported.

```
In [21]: # Import libraries necessary for this project
         import numpy as np
         import pandas as pd
         import seaborn as sns
         import matplotlib.pyplot as plt
         from IPython.display import display # Allows the use of display() for DataFrames

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

         # Pretty display for notebooks
         %matplotlib inline

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

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

1.4 Data Exploration

In this section, you will begin exploring the data through visualizations and code to understand how each feature is related to the others. You will observe a statistical description of the dataset, consider the relevance of each feature, and select a few sample data points from the dataset which you will track through the course of this project.

Run the code block below to observe a statistical description of the dataset. Note that the dataset is composed of six important product categories: **'Fresh'**, **'Milk'**, **'Grocery'**, **'Frozen'**, **'Detergents_Paper'**, and **'Delicatessen'**. Consider what each category represents in terms of products you could purchase.

```
In [22]: # Display a description of the dataset
         display(data.describe())
```

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

       Detergents_Paper  Delicatessen
```

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

1.4.1 Implementation: Selecting Samples

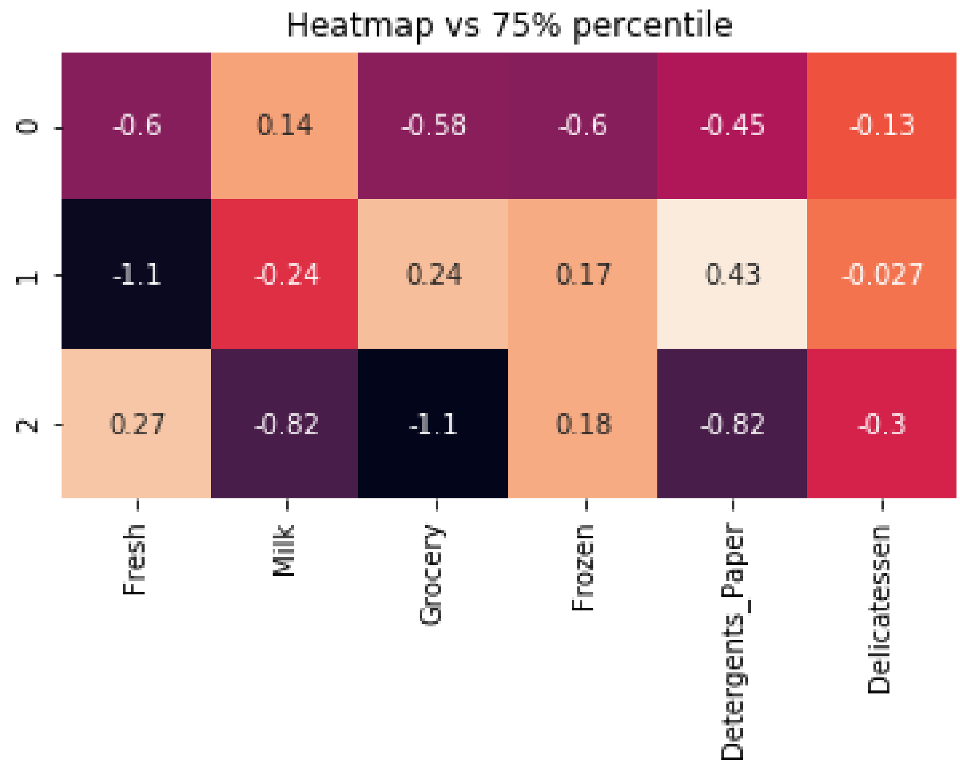
To get a better understanding of the customers and how their data will transform through the analysis, it would be best to select a few sample data points and explore them in more detail. In the code block below, add **three** indices of your choice to the `indices` list which will represent the customers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

In [23]:
```
# TODO: Select three indices of your choice you wish to sample from the dataset
indices = [5, 10, 75]

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

plt.axes().set_title("Heatmap vs 75% percentile")
sns.heatmap((samples-data.quantile(q=0.75))/data.std(ddof=0), annot=True, cbar=False, s
```

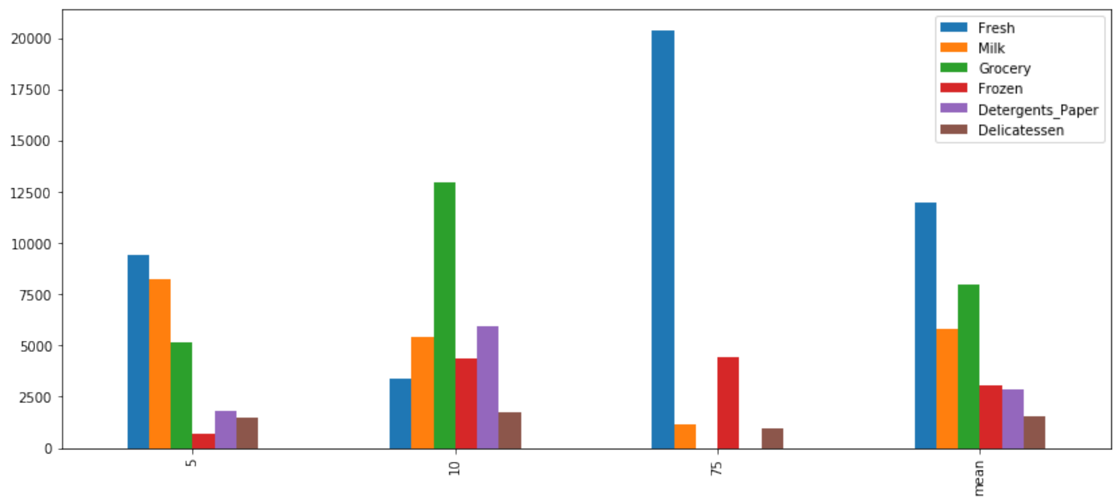
```
Chosen samples of wholesale customers dataset:
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	9413	8259	5126	666	1795	1451
1	3366	5403	12974	4400	5977	1744
2	20398	1137	3	4407	3	975

Out[23]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8ed0f60588>
```




```
In [24]: #visualizing sample points with the datasets mean
         import seaborn as sns
         samples_bar = samples.append(data.describe().loc['mean'])
         samples_bar.index = indices + ['mean']
         _ = samples_bar.plot(kind='bar', figsize=(14,6))
```



1.4.2 Question 1

Consider the total purchase cost of each product category and the statistical description of the dataset above for your sample customers.

- What kind of establishment (customer) could each of the three samples you've chosen represent?

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

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

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

Answer:

Sample 0: This establishments has a limited amount of frozen food and a lot of fresh food and milk. Also the amount of grocery a little above average. The quantity of detergent paper and delicatessen is a bit below average. Looking at these statistics the establishment looks like a restaurant that sells fresh food. But since the volumes are below mean it looks more like an independent establishment. As a whole the sample looks like an independent restaurant.

Sample 1: The establishments seems to have a pretty good stock of all the products with a large proportion of grocery and a somewhat lower proportion of fresh food. It indicates that the setup is some sort of supermarket.

Sample 2: The setup has a vary large stock of fresh food and a resonable stock of frozen food. Also the volume of other products is pretty low. The establishments looks like a supplier of fresh food.

1.4.3 Implementation: Feature Relevance

One interesting thought to consider is if one (or more) of the six product categories is actually relevant for understanding customer purchasing. That is to say, is it possible to determine whether customers purchasing some amount of one category of products will necessarily purchase some proportional amount of another category of products? We can make this determination quite easily by training a supervised regression learner on a subset of the data with one feature removed, and then score how well that model can predict the removed feature.

In the code block below, you will need to implement the following: - Assign `new_data` a copy of the data by removing a feature of your choice using the `DataFrame.drop` function. - Use `sklearn.cross_validation.train_test_split` to split the dataset into training and testing sets. - Use the removed feature as your target label. Set a `test_size` of `0.25` and set a `random_state`. - Import a decision tree regressor, set a `random_state`, and fit the learner to the training data. - Report the prediction score of the testing set using the regressor's `score` function.

```
In [25]: from sklearn.cross_validation import train_test_split
         from sklearn.tree import DecisionTreeRegressor

         # TODO: Make a copy of the DataFrame, using the 'drop' function to drop the given featu
         new_data = data.drop(['Detergents_Paper'], axis=1, inplace = False)

         # TODO: Split the data into training and testing sets(0.25) using the given feature as
         # Set a random state.
         X_train, X_test, y_train, y_test = train_test_split(new_data, data['Detergents_Paper'],

         # TODO: Create a decision tree regressor and fit it to the training set
         regressor = DecisionTreeRegressor(random_state=0)
         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: ", score)
```

```
Score:  0.728655181254
```

1.4.4 Question 2

- Which feature did you attempt to predict?
- What was the reported prediction score?
- Is this feature necessary for identifying customers' spending habits?

Hint: The coefficient of determination, `R^2`, is scored between 0 and 1, with 1 being a perfect fit. A negative `R^2` implies the model fails to fit the data. If you get a low score for a particular feature, that lends us to beleive that that feature point is hard to predict using the other features, thereby making it an important feature to consider when considering relevance.

Answer:

Feature Predicted: Detergents_Paper

Prediction Score: 0.729

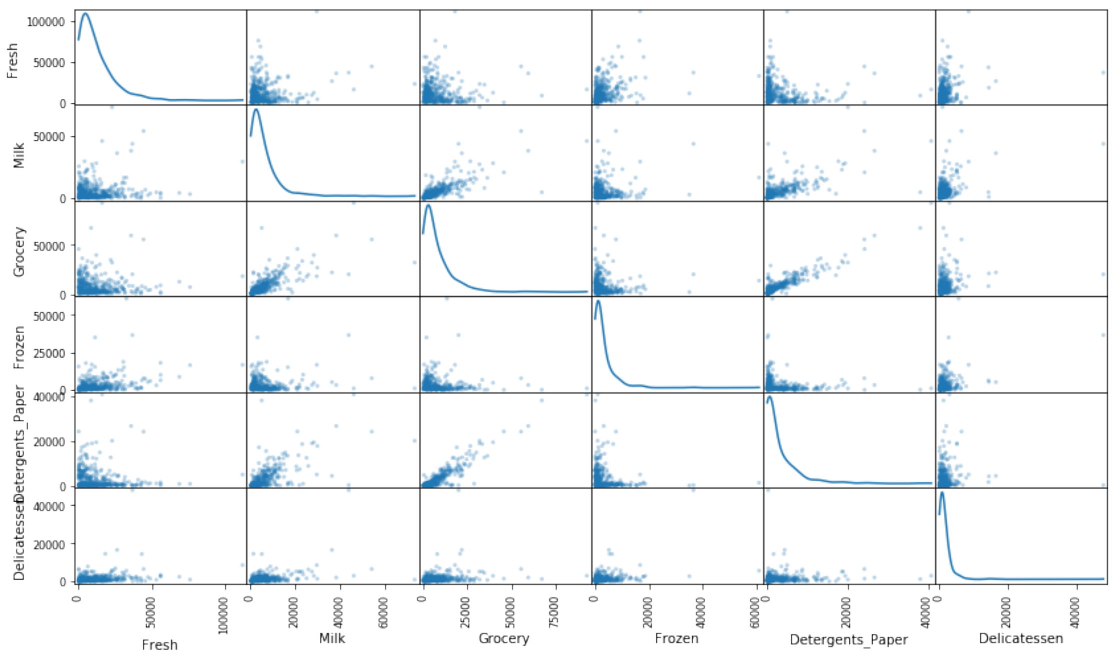
R2 is the coefficient of determination and the score for Detergents_Paper is a significant positive score (within 0 and 1), thus this means that the Detergents_Paper feature could be predicted by other features. Detergents_Paper in itself provides the low information gain and hence it is least useful in identifying customers' spending habits.

1.4.5 Visualize Feature Distributions

To get a better understanding of the dataset, we can construct a scatter matrix of each of the six product features present in the data. If you found that the feature you attempted to predict above is relevant for identifying a specific customer, then the scatter matrix below may not show any correlation between that feature and the others. Conversely, if you believe that feature is not relevant for identifying a specific customer, the scatter matrix might show a correlation between that feature and another feature in the data. Run the code block below to produce a scatter matrix.

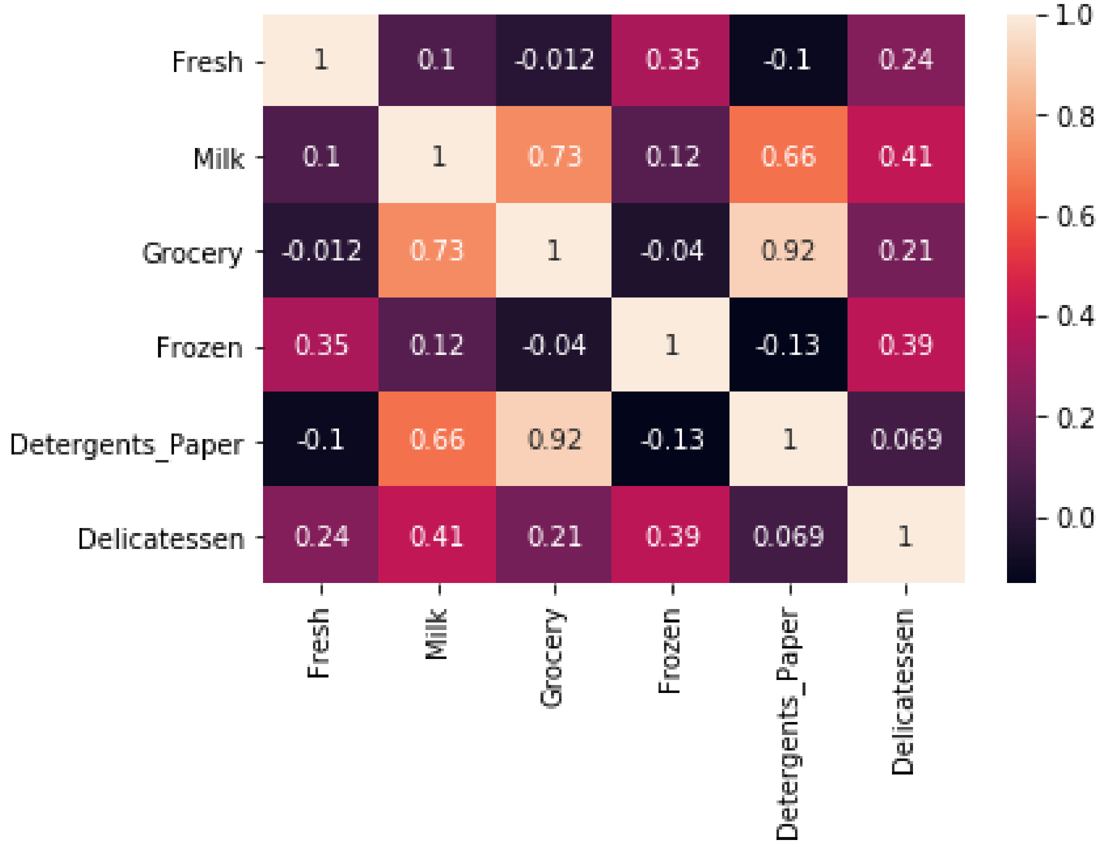
```
In [26]: # Produce a scatter matrix for each pair of features in the data
         pd.scatter_matrix(data, alpha = 0.3, figsize = (14,8), diagonal = 'kde');
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:2: FutureWarning: pandas.scatter_ma
```




```
In [27]: sns.heatmap(data.corr(), annot=True)
```

```
Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8eced75d68>
```



1.4.6 Question 3

- Using the scatter matrix as a reference, discuss the distribution of the dataset, specifically talk about the normality, outliers, large number of data points near 0 among others. If you need to sepearate out some of the plots individually to further accentuate your point, you may do so as well.
- Are there any pairs of features which exhibit some degree of correlation?
- Does this confirm or deny your suspicions about the relevance of the feature you attempted to predict?
- How is the data for those features distributed?

Hint: Is the data normally distributed? Where do most of the data points lie? You can use corr() to get the feature correlations and then visualize them using a heatmap(the data that would be fed into the heatmap would be the correlation values, for eg: `data.corr()`) to gain further insight.

Answer:
There are three pair of features that particularly show a degree of correlation.
Milk and Detergents_Paper: linear correlation with coefficient of 0.66
Grocery and Detergents_Paper: linear correlation with coefficient of 0.92
Milk and Grocery: linear correlation with coefficient of 0.73

Detergent_Paper is strongly correlated to Milk and Grocery and therefore has very little information gain. Detergent_Paper in turn does not contribute much in finding customer segments. This confirms the prediction score that we calculated in previous step.

The data for the pairs mentioned above follow a linear relation, y = mx + c. Overall when we look at the scatter matrix, we see that the data points majorly lie towards origin. The dataset is highly skewed and it is noticed that the median falls below the mean. This means that majority of market segment or customers is owned by smaller outlets.

1.5 Data Preprocessing

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

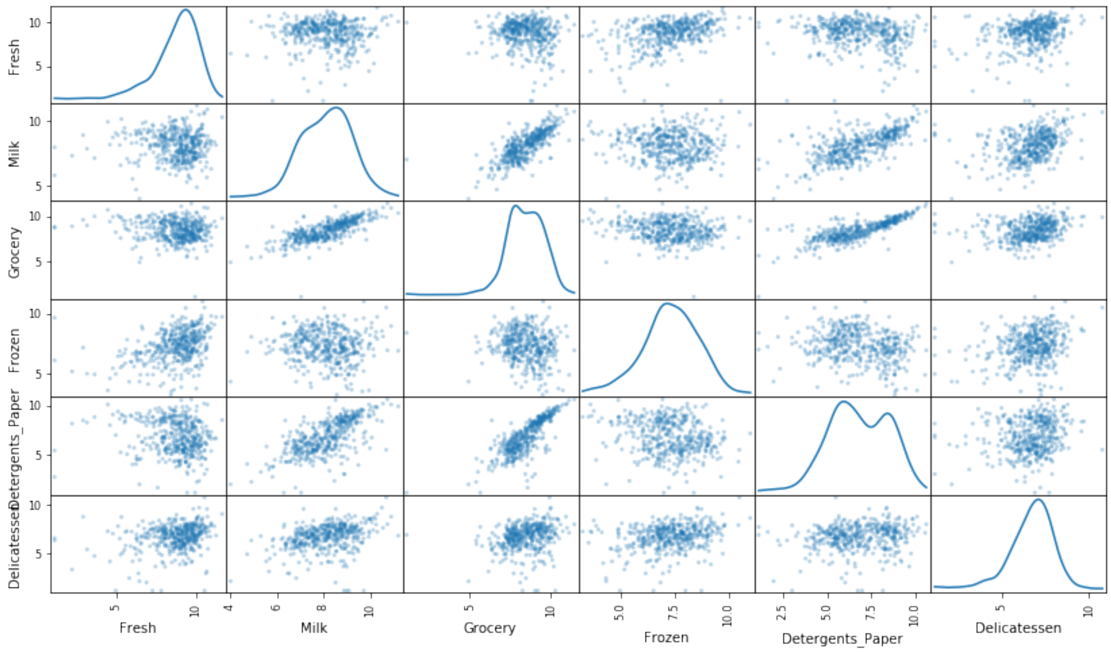
1.5.1 Implementation: Feature Scaling

If data is not normally distributed, especially if the mean and median vary significantly (indicating a large skew), it is most often appropriate to apply a non-linear scaling — particularly for financial data. One way to achieve this scaling is by using a Box-Cox test, which calculates the best power transformation of the data that reduces skewness. A simpler approach which can work in most cases would be applying the natural logarithm.

In the code block below, you will need to implement the following: - Assign a copy of the data to `log_data` after applying logarithmic scaling. Use the `np.log` function for this. - Assign a copy of the sample data to `log_samples` after applying logarithmic scaling. Again, use `np.log`.

```
In [28]: # TODO: Scale the data using the natural logarithm
         log_data = np.log(data)

         # TODO: Scale the sample data using the natural logarithm
         log_samples = np.log(samples)

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

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:8: FutureWarning: pandas.scatter_ma
```



1.5.2 Observation

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

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

```
In [29]: # Display the log-transformed sample data
         display(log_samples)
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	9.149847	9.019059	8.542081	6.501290	7.492760	7.280008
1	8.121480	8.594710	9.470703	8.389360	8.695674	7.463937
2	9.923192	7.036148	1.098612	8.390949	1.098612	6.882437

1.5.3 Implementation: Outlier Detection

Detecting outliers in the data is extremely important in the data preprocessing step of any analysis. The presence of outliers can often skew results which take into consideration these data points. There are many "rules of thumb" for what constitutes an outlier in a dataset. Here, we will use Tukey's Method for identfying outliers: An *outlier step* is calculated as 1.5 times the interquartile range (IQR). A data point with a feature that is beyond an outlier step outside of the IQR for that feature is considered abnormal.

In the code block below, you will need to implement the following: - Assign the value of the 25th percentile for the given feature to `Q1`. Use `np.percentile` for this. - Assign the value of the 75th percentile for the given feature to `Q3`. Again, use `np.percentile`. - Assign the calculation of an outlier step for the given feature to `step`. - Optionally remove data points from the dataset by adding indices to the `outliers` list.

NOTE: If you choose to remove any outliers, ensure that the sample data does not contain any of these points!
Once you have performed this implementation, the dataset will be stored in the variable `good_data`.

```
In [30]: # OPTIONAL: Select the indices for data points you wish to remove
         outliers  = []

         # For each feature find the data points with extreme high or low values
         for feature in log_data.keys():

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

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

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

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

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

```
Data points considered outliers for the feature 'Fresh':
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
65	4.442651	9.950323	10.732651	3.583519	10.095388	7.260523
66	2.197225	7.335634	8.911530	5.164786	8.151333	3.295837
81	5.389072	9.163249	9.575192	5.645447	8.964184	5.049856
95	1.098612	7.979339	8.740657	6.086775	5.407172	6.563856
96	3.135494	7.869402	9.001839	4.976734	8.262043	5.379897
128	4.941642	9.087834	8.248791	4.955827	6.967909	1.098612
171	5.298317	10.160530	9.894245	6.478510	9.079434	8.740337
193	5.192957	8.156223	9.917982	6.865891	8.633731	6.501290
218	2.890372	8.923191	9.629380	7.158514	8.475746	8.759669
304	5.081404	8.917311	10.117510	6.424869	9.374413	7.787382

305	5.493061	9.468001	9.088399	6.683361	8.271037	5.351858
338	1.098612	5.808142	8.856661	9.655090	2.708050	6.309918
353	4.762174	8.742574	9.961898	5.429346	9.069007	7.013016
355	5.247024	6.588926	7.606885	5.501258	5.214936	4.844187
357	3.610918	7.150701	10.011086	4.919981	8.816853	4.700480
412	4.574711	8.190077	9.425452	4.584967	7.996317	4.127134

Data points considered outliers for the feature 'Milk':

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
86	10.039983	11.205013	10.377047	6.894670	9.906981	6.805723
98	6.220590	4.718499	6.656727	6.796824	4.025352	4.882802
154	6.432940	4.007333	4.919981	4.317488	1.945910	2.079442
356	10.029503	4.897840	5.384495	8.057377	2.197225	6.306275

Data points considered outliers for the feature 'Grocery':

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
75	9.923192	7.036148	1.098612	8.390949	1.098612	6.882437
154	6.432940	4.007333	4.919981	4.317488	1.945910	2.079442

Data points considered outliers for the feature 'Frozen':

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
38	8.431853	9.663261	9.723703	3.496508	8.847360	6.070738
57	8.597297	9.203618	9.257892	3.637586	8.932213	7.156177
65	4.442651	9.950323	10.732651	3.583519	10.095388	7.260523
145	10.000569	9.034080	10.457143	3.737670	9.440738	8.396155
175	7.759187	8.967632	9.382106	3.951244	8.341887	7.436617
264	6.978214	9.177714	9.645041	4.110874	8.696176	7.142827
325	10.395650	9.728181	9.519735	11.016479	7.148346	8.632128
420	8.402007	8.569026	9.490015	3.218876	8.827321	7.239215
429	9.060331	7.467371	8.183118	3.850148	4.430817	7.824446
439	7.932721	7.437206	7.828038	4.174387	6.167516	3.951244

Data points considered outliers for the feature 'Detergents_Paper':

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
75	9.923192	7.036148	1.098612	8.390949	1.098612	6.882437
161	9.428190	6.291569	5.645447	6.995766	1.098612	7.711101

Data points considered outliers for the feature 'Delicatessen':

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
66	2.197225	7.335634	8.911530	5.164786	8.151333	3.295837
109	7.248504	9.724899	10.274568	6.511745	6.728629	1.098612
128	4.941642	9.087834	8.248791	4.955827	6.967909	1.098612
137	8.034955	8.997147	9.021840	6.493754	6.580639	3.583519
142	10.519646	8.875147	9.018332	8.004700	2.995732	1.098612
154	6.432940	4.007333	4.919981	4.317488	1.945910	2.079442
183	10.514529	10.690808	9.911952	10.505999	5.476464	10.777768
184	5.789960	6.822197	8.457443	4.304065	5.811141	2.397895
187	7.798933	8.987447	9.192075	8.743372	8.148735	1.098612
203	6.368187	6.529419	7.703459	6.150603	6.860664	2.890372
233	6.871091	8.513988	8.106515	6.842683	6.013715	1.945910
285	10.602965	6.461468	8.188689	6.948897	6.077642	2.890372
289	10.663966	5.655992	6.154858	7.235619	3.465736	3.091042
343	7.431892	8.848509	10.177932	7.283448	9.646593	3.610918

1.5.4 Question 4

- Are there any data points considered outliers for more than one feature based on the definition above?
- Should these data points be removed from the dataset?
- If any data points were added to the `outliers` list to be removed, explain why.

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

Answer:

The below data points are outliers as these data points lie beyond an outlier step outside of the IQR: - 65 - Frozen and Fresh - 66 - Delicatessen and Fresh - 75 - Detergents_Paper and Grocery - 128 - Delicatessen and Fresh - 154 - Delicatessen, Milk and Grocery

These data points should be removed from the dataset as they often skew results of the model which take into consideration these data points.

The data points which are an outlier step outside of the IQR are added to the outliers list and are removed from the complete list of data points considered for model training. These data points skew the models performance and does not help in enhancing the model performance. There are 42 outliers, in 440 samples, nearly 10 percentage of the total number. If we remove all the outlier,we would lose a lots of information. Hence we find samples that are considered outliers for more than one feature, in this case 5 samples. We remove these 5 samples instead of removing all the outlier to keep the information in the samples and make sure we have enough samples to analyse.

1.6 Feature Transformation

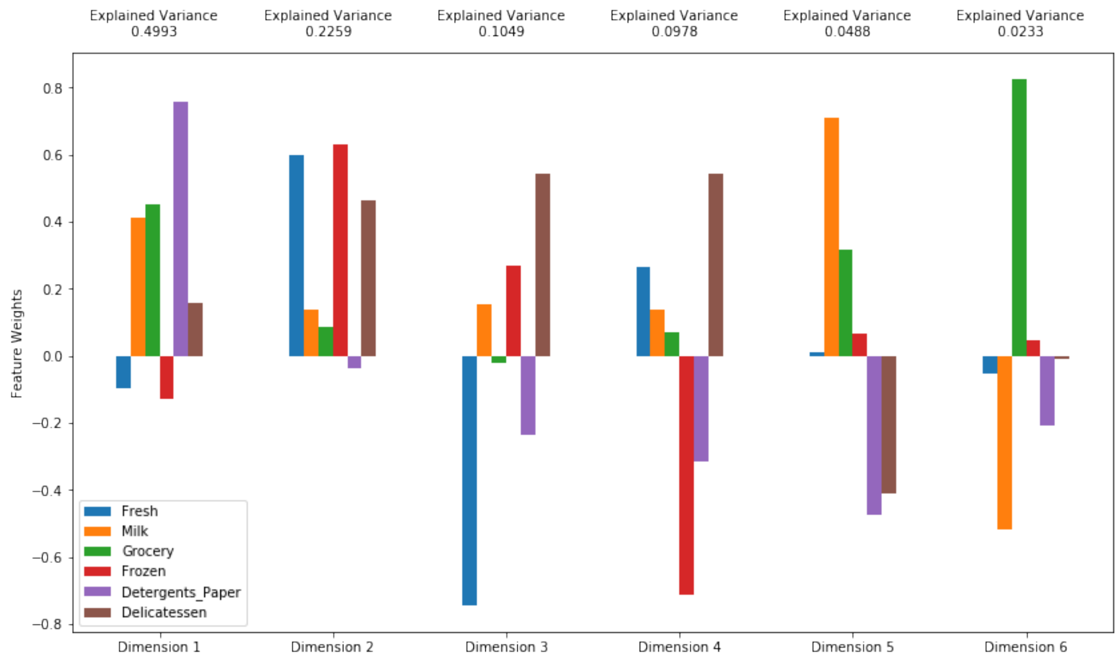
In this section you will use principal component analysis (PCA) to draw conclusions about the underlying structure of the wholesale customer data. Since using PCA on a dataset calculates the dimensions which best maximize variance, we will find which compound combinations of features best describe customers.

1.6.1 Implementation: PCA

Now that the data has been scaled to a more normal distribution and has had any necessary outliers removed, we can now apply PCA to the `good_data` to discover which dimensions about the data best maximize the variance of features involved. In addition to finding these dimensions, PCA will also report the *explained variance ratio* of each dimension — how much variance within the data is explained by that dimension alone. Note that a component (dimension) from PCA can be considered a new "feature" of the space, however it is a composition of the original features present in the data.

In the code block below, you will need to implement the following: - Import `sklearn.decomposition.PCA` and assign the results of fitting PCA in six dimensions with `good_data` to `pca`. - Apply a PCA transformation of `log_samples` using `pca.transform`, and assign the results to `pca_samples`.

```
In [31]: from sklearn.decomposition import PCA

         # TODO: Apply PCA by fitting the good data with the same number of dimensions as featur
         pca = PCA(n_components=6)
         pca.fit(good_data)

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

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



1.6.2 Question 5

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

Hint: A positive increase in a specific dimension corresponds with an *increase* of the *positive-weighted* features and a *decrease* of the *negative-weighted* features. The rate of increase or decrease is based on the individual feature weights.

Answer:

Total variance of first 2 components: 72.5%

Total variance of first 4 components: 92.8%

1st Dimension: It provides maximum information gain for Detergent Paper. It also provides some information about Milk and Grocery. Additionally we gain very little information about Delicatessen. It badly fails to predict Fresh and Frozen for which we need additional dimension. It could represent supermarket category.

2nd Dimension: It provides significant information about Fresh and Frozen categories and overcomes the shortcoming of 1st dimension. We also gain good amount of information about Delicatessen. There is small gain for Milk and Grocery and a small loss for Detergent Paper. It could represent restaurant category.

3rd Dimension: It provides information about Fresh and to some extent information about Delicatessen. For other categories there is loss in information. It could represent Fresh item stores with some groceries.

4th Dimension: It provides information about Frozen and to some extent information about Detergent Paper. For other categories there is loss in information. It could represent frozen item suppliers.

1.6.3 Observation

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

In [32]:
```
# Display sample log-data after having a PCA transformation applied
display(pd.DataFrame(np.round(pca_samples, 4), columns = pca_results.index.values))
```

```
   Dimension 1  Dimension 2  Dimension 3  Dimension 4  Dimension 5  \
0       1.1335      -0.1257      -0.1789       0.8899       0.0844
1       2.1793       0.5069       0.8243      -1.0031      -0.4516
2      -8.2757       0.6801       0.8810       0.7494      -0.3550

   Dimension 6
0      -0.5694
1       0.3107
2      -4.3153
```

1.6.4 Implementation: Dimensionality Reduction

When using principal component analysis, one of the main goals is to reduce the dimensionality of the data — in effect, reducing the complexity of the problem. Dimensionality reduction comes at a cost: Fewer dimensions used implies less of the total variance in the data is being explained. Because of this, the *cumulative explained variance ratio* is extremely important for knowing how many dimensions are necessary for the problem. Additionally, if a signifiant amount of variance is explained by only two or three dimensions, the reduced data can be visualized afterwards.

In the code block below, you will need to implement the following: - Assign the results of fitting PCA in two dimensions with `good_data` to `pca`. - Apply a PCA transformation of `good_data` using `pca.transform`, and assign the results to `reduced_data`. - Apply a PCA transformation of `log_samples` using `pca.transform`, and assign the results to `pca_samples`.

In [33]:
```
# TODO: Apply PCA by fitting the good data with only two dimensions
pca = PCA(n_components=2)
pca.fit(good_data)

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

# TODO: Transform log_samples using the PCA fit above
```

```
pca_samples = pca.transform(log_samples)

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

1.6.5 Observation

Run the code below to see how the log-transformed sample data has changed after having a PCA transformation applied to it using only two dimensions. Observe how the values for the first two dimensions remains unchanged when compared to a PCA transformation in six dimensions.

```
In [34]: # Display sample log-data after applying PCA transformation in two dimensions
         display(pd.DataFrame(np.round(pca_samples, 4), columns = ['Dimension 1', 'Dimension 2']
```

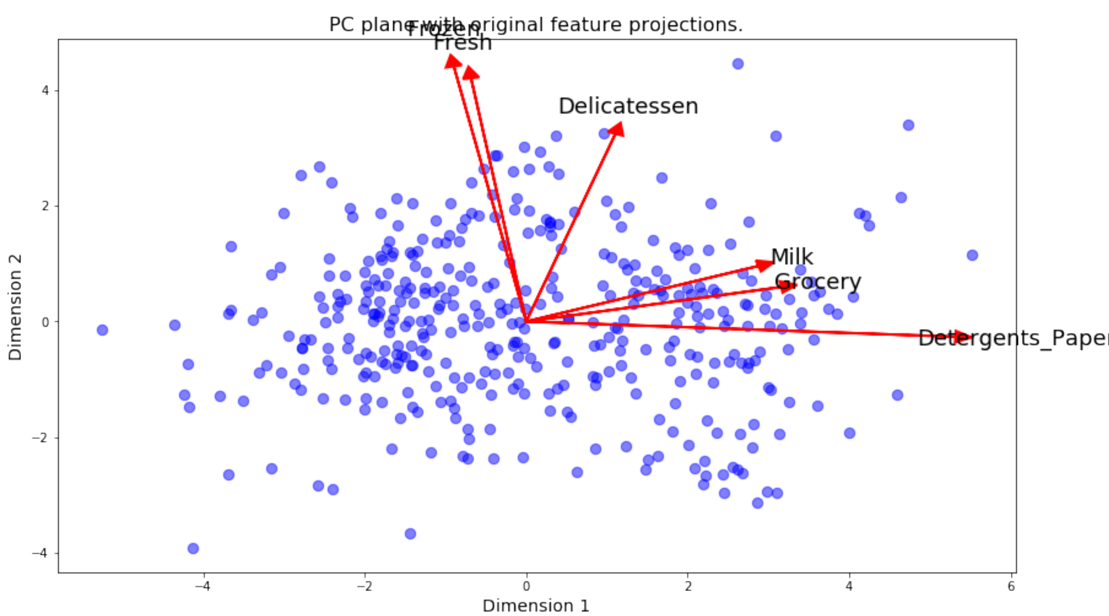
	Dimension 1	Dimension 2
0	1.1335	-0.1257
1	2.1793	0.5069
2	-8.2757	0.6801

1.7 Visualizing a Biplot

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

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

```
In [35]: # Create a biplot
         vs.biplot(good_data, reduced_data, pca)

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8ed0b8b198>
```



1.7.1 Observation

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

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

1.8 Clustering

In this section, you will choose to use either a K-Means clustering algorithm or a Gaussian Mixture Model clustering algorithm to identify the various customer segments hidden in the data. You will then recover specific data points from the clusters to understand their significance by transforming them back into their original dimension and scale.

1.8.1 Question 6

- What are the advantages to using a K-Means clustering algorithm?
- What are the advantages to using a Gaussian Mixture Model clustering algorithm?
- Given your observations about the wholesale customer data so far, which of the two algorithms will you use and why?

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

Answer:

K-Means clustering algorithm is simple to use as it takes minimal parameters such as number of clusters and maximum iterations. Every data point is hard bound to one cluster or the other. The computations involved is fast and hence it suits well for large data sets. K Means works well when the data clusters are relatively simple in shape, well separated and distinct - so that the clustering is accurate as K-Means does the hard assignment, we are certain each point belongs to which cluster.This algorithm requires the number of clusters to be specified.

Gaussian Mixture Model clustering algorithm is used to soft bound data points to clusters. It assigns probabilities to each data point that is a reflection of there affinity to different clusters. It works with spherical as well as non-spherical clusters.

We will use Gaussian Mixture Model clustering algorithm for these reasons:Data is uniformly distributed and there is not hard bound of majority data points to any particular category.

1.8.2 Implementation: Creating Clusters

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

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

```
In [36]: from sklearn.mixture import GaussianMixture
         from sklearn.metrics import silhouette_score

         def getGaussianMixtureScore(k):
             global clusterer, preds, centers, sample_preds

             # TODO: Apply your clustering algorithm of choice to the reduced data
             clusterer = GaussianMixture(n_components=2, random_state=0)
             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 = silhouette_score(reduced_data,preds)
             return score

         silhouette_scores = pd.DataFrame(columns=['Score'])
         silhouette_scores.columns.name = 'Cluster Size'

         for k in range(2, 12):
             score = getGaussianMixtureScore(k)
             silhouette_scores = silhouette_scores.append(pd.DataFrame([score],columns=['Score']
```

```
         display(silhouette_scores)
```

```
Cluster Size     Score
2             0.446754
3             0.446754
4             0.446754
5             0.446754
6             0.446754
```

```
7              0.446754
8              0.446754
9              0.446754
10             0.446754
11             0.446754
```

1.8.3 Question 7

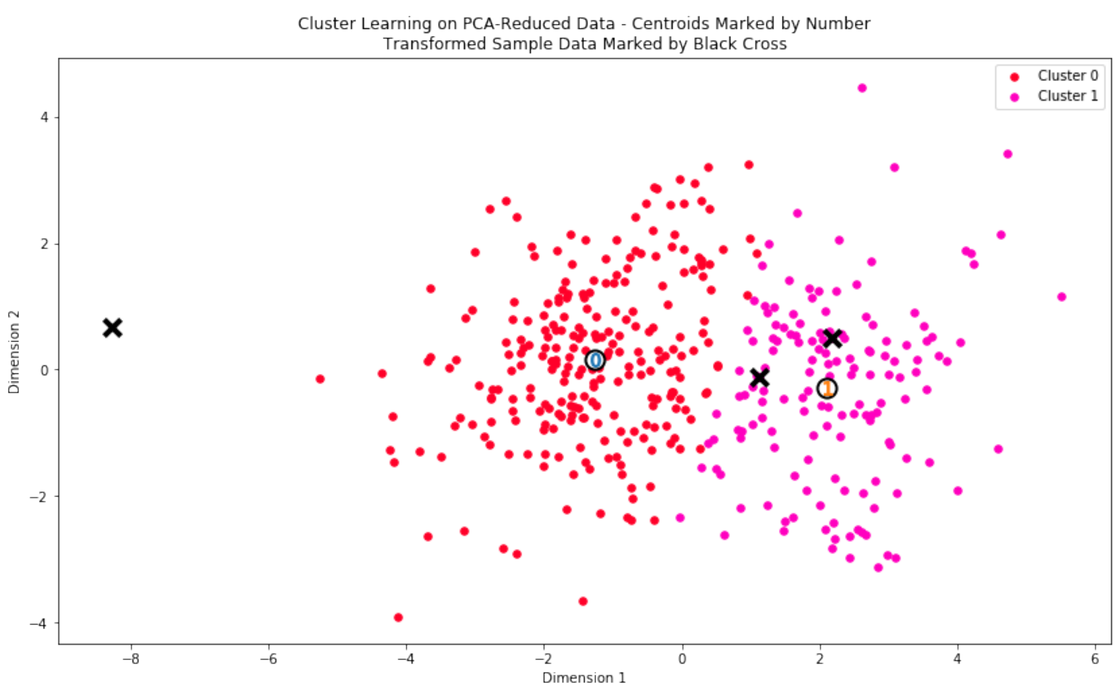
- Report the silhouette score for several cluster numbers you tried.
- Of these, which number of clusters has the best silhouette score?

Answer:
For silhouette score for several cluster numbers please refer the Dataframe 'silhouette_scores' displayed above.
Best silhouette score corresponds to Gaussian Mixture Model with 2 clusters.

1.8.4 Cluster Visualization

Once you've chosen the optimal number of clusters for your clustering algorithm using the scoring metric above, you can now visualize the results by executing the code block below. Note that, for experimentation purposes, you are welcome to adjust the number of clusters for your clustering algorithm to see various visualizations. The final visualization provided should, however, correspond with the optimal number of clusters.

```
In [37]: getGaussianMixtureScore(2)

         # Display the results of the clustering from implementation
         vs.cluster_results(reduced_data, preds, centers, pca_samples)
```



1.8.5 Implementation: Data Recovery

Each cluster present in the visualization above has a central point. These centers (or means) are not specifically data points from the data, but rather the *averages* of all the data points predicted in the respective clusters. For the problem of creating customer segments, a cluster's center point corresponds to *the average customer of that segment*. Since the data is currently reduced in dimension and scaled by a logarithm, we can recover the representative customer spending from these data points by applying the inverse transformations.

In the code block below, you will need to implement the following: - Apply the inverse transform to `centers` using `pca.inverse_transform` and assign the new centers to `log_centers`. - Apply the inverse function of `np.log` to `log_centers` using `np.exp` and assign the true centers to `true_centers`.

In [38]:
```
# 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	9494.0	2049.0	2598.0	2203.0	337.0	796.0
Segment 1	5219.0	7671.0	11403.0	1079.0	4413.0	1099.0

1.8.6 Question 8

- Consider the total purchase cost of each product category for the representative data points above, and reference the statistical description of the dataset at the beginning of this project(specifically looking at the mean values for the various feature points). What set of establishments could each of the customer segments represent?

Hint: A customer who is assigned to `'Cluster X'` should best identify with the establishments represented by the feature set of `'Segment X'`. Think about what each segment represents in terms their values for the feature points chosen. Reference these values with the mean values to get some perspective into what kind of establishment they represent.

Answer:

Cluster 0: The value of Fresh category dominates in this cluster even though it is a bit less than the mean of overall population. This suggests that cluster 0 represents an establishment that serves fresh food, something like a restaurant. In the initial Data Exploration section also we see that the numbers for restaurant looks consistent with cluster 0.

Cluster 1: The values of Milk and Grocery dominate here and these values are well above the mean we saw in Data Exploration section. This suggests that cluster 1 represents an establishment that deals in bulk items, something like a supermarket.

1.8.7 Question 9

- For each sample point, which customer segment from* **Question 8** *best represents it?
- Are the predictions for each sample point consistent with this?*

Run the code block below to find which cluster each sample point is predicted to be.

```
In [39]: # Display the predictions
         for i, pred in enumerate(sample_preds):
             print("Sample point", i, "predicted to be in Cluster", pred)
```

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

Answer:

Sample 0: - Model predicted that the sample belongs to the category of supermarket but in the previous assessment we attributed the sample to belong to the category of restaurants. The models prediction is inconsistent with what we predicted the sample to be. This might be because we attributed a abdunance of Milk and Fresh items to restaurants only.

Sample 1: - Model predicted that the sample belongs to the category of supermarket and in the previous assessment we attributed the sample to belong to the category of supermarkets. The models prediction is consistent with what we predicted the sample to be. This might be because we attributed a abdunance of Grocery to supermarkets.

Sample 2: - Model predicted that the sample belongs to the category of restaurant but in the previous assessment we attributed the sample to belong to the category of bulk suppliers. The models prediction is inconsistent with what we predicted the sample to be. This might be because we attributed a abdunance of Fresh items to suppliers.

```
Out of 3 sample data points we see that the models prediction is consistent with our inital pred
```

1.9 Conclusion

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

1.9.1 Question 10

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

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

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

Answer:

We have 2 customer segments. Segment 0 which corresponds to restaurants and segment 1 which corresponds to supermarkets. Segement 0 customers would like to keep a fresh supply of food and hence it would most likely prefer 5 days a week delivery service. Segment 1 customers buy a variety of items that are non perishable and hence can work with 3 days a week delivery service too.

The wholesale distributor can run A/B tests. He can select a subset of customers from both segments, run an experiment of 3 days a week delivery service experiment and then evaluate the results. This will help him identify the segment that reacts positively to the change in delivery service. He can then make better decision that will benefit the business. This approach is better than changing the delivery service for all the customers.

1.9.2 Question 11

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

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

Answer:

We can use a combination of unsupervised and supervised algorithms to classify new customers.

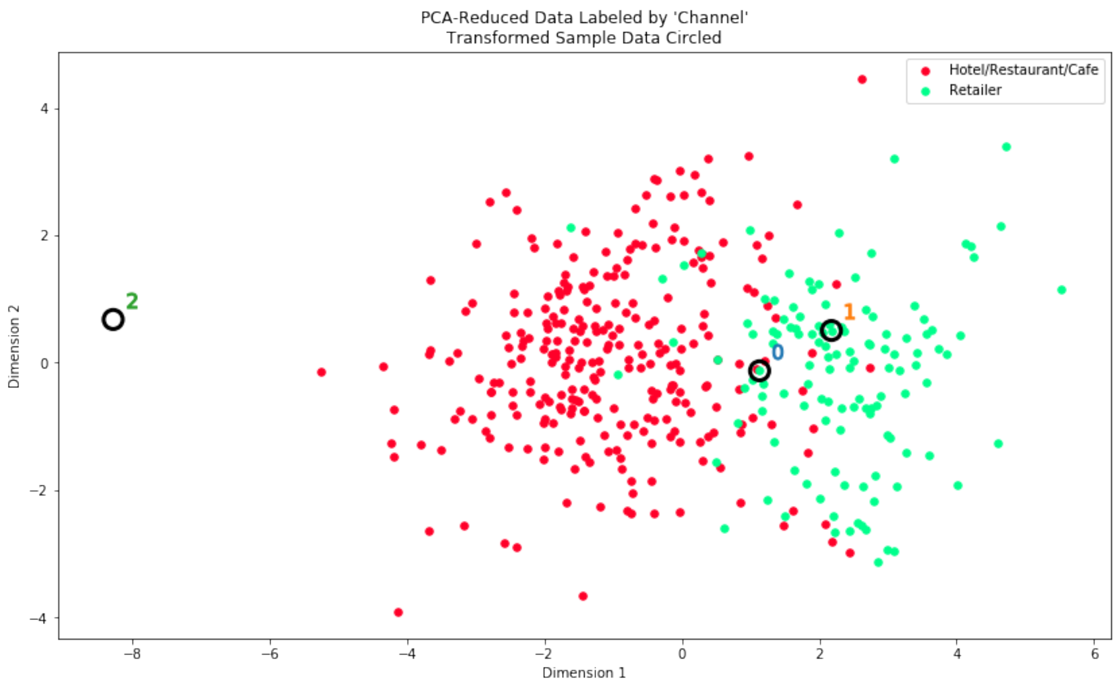
Steps: - Unsupervised step. Use unsupervised technique like Gaussian Mixture Model to find clusters in the unlabelled data set. The predicted cluster for each data point is then added as an engineered feature 'Customer Segment' to the data set. The value can be 0 and 1 for segment 0 and segment 1 respectively. - Supervised step. Use supervised technique like SVM with 'Customer Segment' as target variable. - Use the supervised model to then predict the customer segment for each new customer.

1.9.3 Visualizing Underlying Distributions

At the beginning of this project, it was discussed that the `'Channel'` and `'Region'` features would be excluded from the dataset so that the customer product categories were emphasized in the analysis. By reintroducing the 'Channel' feature to the dataset, an interesting structure emerges when considering the same PCA dimensionality reduction applied earlier to the original dataset.

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

In [40]:
```
# Display the clustering results based on 'Channel' data
vs.channel_results(reduced_data, outliers, pca_samples)
```



1.9.4 Question 12

- How well does the clustering algorithm and number of clusters you've chosen compare to this underlying distribution of Hotel/Restaurant/Cafe customers to Retailer customers?
- Are there customer segments that would be classified as purely 'Retailers' or 'Hotels/Restaurants/Cafes' by this distribution?
- Would you consider these classifications as consistent with your previous definition of the customer segments?

Answer:

- The clustering algorithm and number of clusters we have chosen is able to establish the relations as evident in the underlying distribution of Hotel/Restaurant/Cafe customers to Retailer customers. Althought the algorithm fails to identify the retailers that lie in Hotel/Restaurant/Cafe cluster.

- There is no well defined separation between 'Retailers' and 'Hotels/Restaurants/Cafes' by this distribution. However we can say that customers with high values of Dimension 1 and Dimension2 belong to 'Retailers'. Similarly customers with low values of Dimension 1 and Dimension 2 belong to 'Hotels/Restaurants/Cafes'.
- Yes these classifications are consistent with the previous definition of the customer segments. We attributed segment 0 to be restaurant or cafes. We didn't specifically mention hotels though. Segment 1 we attributed to supermarkets which are kind of retailers.

  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.