customer_segments

September 7, 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 [58]: # Import libraries necessary for this project
         import numpy as np
         import pandas as pd
         from IPython.display import display # Allows the use of display() for DataFrames

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

         # Pretty display for notebooks
         %matplotlib inline

         # Load the wholesale customers dataset
         try:
             data = pd.read_csv("customers.csv")
             data.drop(['Region', 'Channel'], axis = 1, inplace = True)
             print("Wholesale customers dataset has {} samples with {} features each.".format(*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 [59]: # 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 [60]: # TODO: Select three indices of your choice you wish to sample from the dataset
         indices = [1, 11, 111]

         # 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)
```

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

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	7057	9810	9568	1762	3293	1776
1	13146	1124	4523	1420	549	497
2	12579	11114	17569	805	6457	1519

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:

Data Index 1 - This customer purchases adeqate amount of fresh products. Milk uses are extremly high as compare to mean value. Grocery and delicatessen uses are slightly more than average. Frozen products uses are less. Detergent uses are more than average. Use of just sufficient amount of detergent indicates towards restaurants. But fresh products use are just normal but milk products use are extremy high, so this must be a `sweet restaurants` ulilises good amount of grocery and delicatessen.

Data Index 11 - This customer buys fresh material more than average (mean). Milk purchase is very less below 25%. Grocery is in sufficient amount around 50 percentile. Frozen product quantity is very low. Detergents and delicatessen are like negligible compared to average. So I have very strong opinion for this cutomer being a `street vendor` which sells fresh food items (like salad and many more) on daily basis. Uses very low detergent strongly back up this opinion for street vendor (uses one time plates and disposals). Grocery is in sufficient use.

Data Index 111 - This customer has almost all the item categories in large amount (more than average). This could be `SuperMarket (retailer Grocery Store)` based on their higher than average purchase costs across all product categories. The detergents quantity is unexpectedly high as comared to fresh and milk products, so this might also be a `hostel mess` (just a guess).

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

         # TODO: Split the data into training and testing sets(0.25) using the given feature as
         # Set a random state.
         from sklearn.model_selection import train_test_split
         X_train, X_test, y_train, y_test = train_test_split(new_data, target, test_size = 0.25,

         # TODO: Create a decision tree regressor and fit it to the training set
```

```
from sklearn.tree import DecisionTreeRegressor
regressor = DecisionTreeRegressor(random_state = 42)
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)

# Frozen : -0.210135890125
# Grocery : 0.681884008544
```

```
-0.210135890125
```

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:

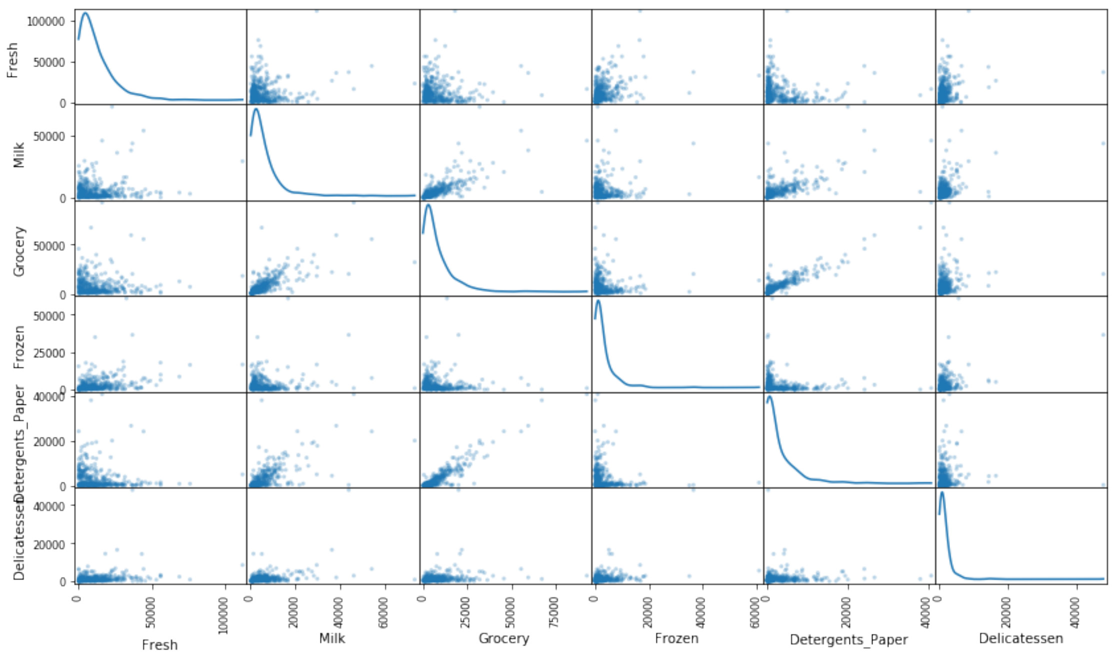
I choose to predict `Frozen`. But the prdiction score is negative `-0.210135890125`. Since `R^2` score comes negative, our model failes to fit the data. This implies that this feature frozen is completely independent and don't have any relationship with other features. Thus removing it, we are depriving the model from very relevent information. This feature provides a lot of information gain. We cannot fit the model with the data without this feature, expecting it to be predicted. Thus it is necessary for identifying customers' spending habits.

On the other hand, I also analysed the relationship of another feature `Grocery` and found it to be having a comparatively good (can say) relationship with other features as `R^2` score is `0.681884008544`. Thus this feature (if like to) can be removed (not recommended) as it is not that much of critical value.

1.4.5 Visualize Feature Distributions

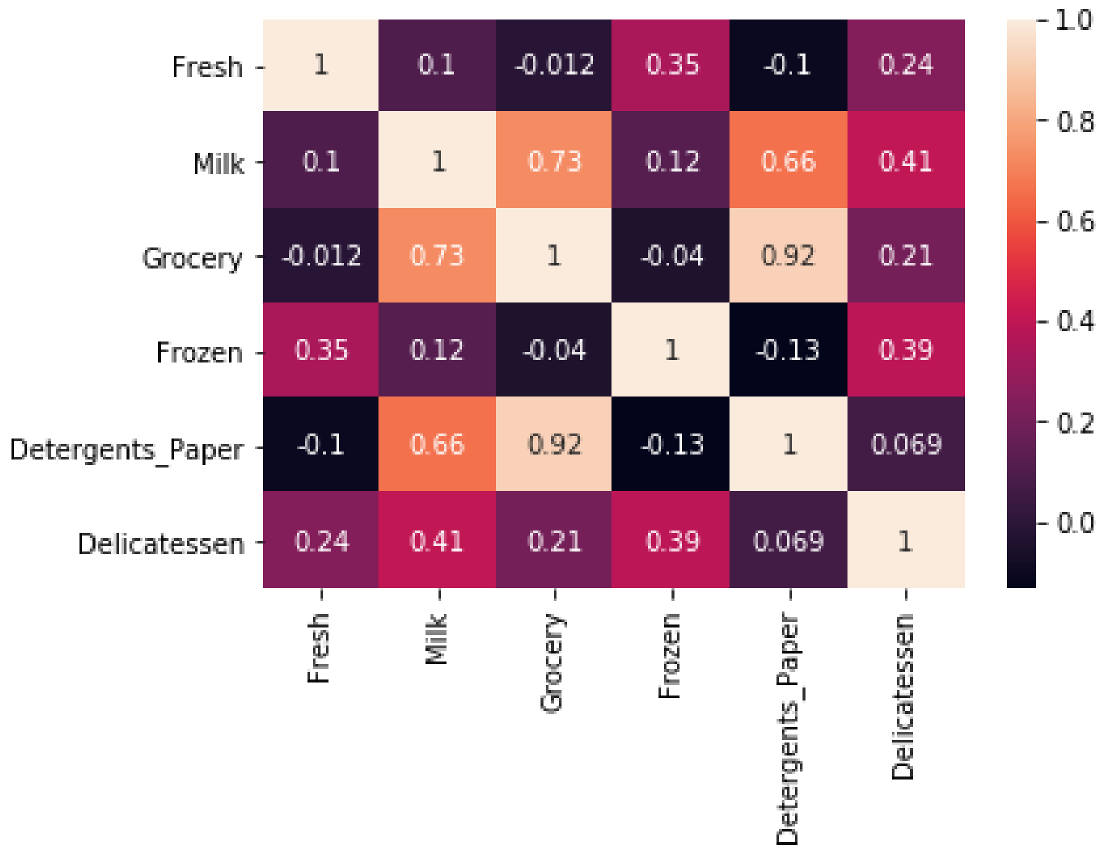
To get a better understanding of the dataset, we can construct a scatter matrix of each of the six product features present in the data. If you found that the feature you attempted to predict above is relevant for identifying a specific customer, then the scatter matrix below may not show any correlation 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 [62]: # Produce a scatter matrix for each pair of features in the data
         pd.plotting.scatter_matrix(data, alpha = 0.3, figsize = (14,8), diagonal = 'kde');
```



In [63]:
```
# Getting the feature correlations and visualize them using a heatmap
import seaborn as sns
sns.heatmap(data.corr(), annot=True)
```

Out[63]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f66684c45c0>
```



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:

We can easily see in scatter plot as well as heat map, there are not much of correlation between almost any features except `Grocery` with `Milk` and `Detergent_paper`. Here Grocery seems to be sharing moderate relationship with milk having correlation score of 0.73 and apparently higher with detergents_paper having correlation score of 0.92. One among them can be excluded (only if required) without losing much of information.

From the density scatter plot we can infer that the data graph for these features are `highly skewed to the right` (positively skewed) or are not normally distributed.

We can depict linear density distributon between features `Grocery` and `Detergents_Paper` from scatter plot which shows that both are correlated and high correlation score from heat map supports it. Also as predicted for previous question, feature `Frozen` correlation scores with the other features are very low or negative, meaning that there is almost no correlation between this and other features.

All the graph shows high density of data close to 0, but few higher data points points sparsely distributed. These data points seems to be `outliers`.

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

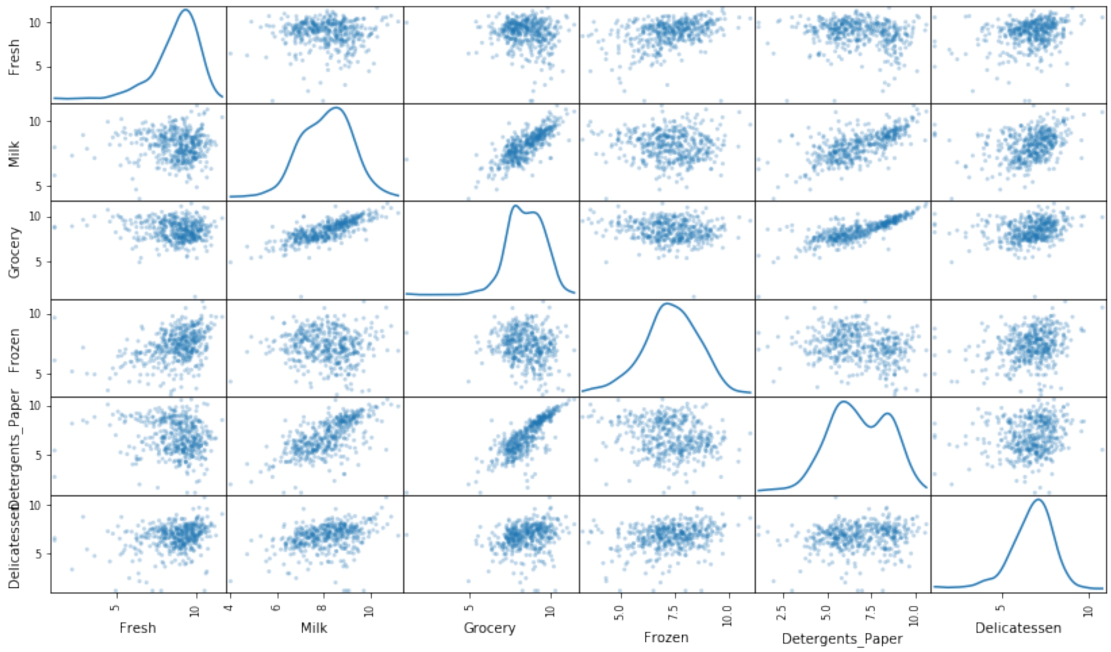
If data is not normally distributed, especially if the mean and median vary significantly (indicating a large skew), it is most often appropriate to apply a non-linear scaling — particularly for financial data. One way to achieve this scaling is by using a Box-Cox test, which calculates the best power 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 [64]: # TODO: Scale the data using the natural logarithm
         log_data = np.log(data)

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

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



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 [65]: # 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	9.483873	7.024649	8.416931	7.258412	6.308098	6.208590
2	9.439784	9.315961	9.773891	6.690842	8.772920	7.325808

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 [66]:
```
from collections import Counter

# For each feature find the data points with extreme high or low values
outliers  = []
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 = (Q3 - Q1) * 1.5

    # Display the outliers
    print("Data points considered outliers for the feature '{}':".format(feature))
    display(log_data[~((log_data[feature] >= Q1 - step) & (log_data[feature] <= Q3 + st
    feature_outliers = log_data.index[~((log_data[feature] >= Q1 - step) & (log_data[fe
    for outlier in feature_outliers: outliers.append(outlier)

# OPTIONAL: Select the indices for data points you wish to remove
count = Counter(outliers)
print("\nTotal outliers:\n", format(Counter(outliers)))

print("\nThe total number of outliers from every features is:", format(sum(Counter(outl

repeated_outliers = Counter(el for el in count.elements() if count[el] > 1)
print("\nThe number of repeating outliers is:", format(len(list(repeated_outliers))))

print("Repeated outliers:", format(list(repeated_outliers)))
display(log_data.iloc[list(repeated_outliers)])

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

# printing the shape of data without outliers
print("\nThe shape of data without outliers is:", format(good_data.shape))
```

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

```
Total outliers:
 Counter({154: 3, 65: 2, 66: 2, 128: 2, 75: 2, 81: 1, 95: 1, 96: 1, 171: 1, 193: 1, 218: 1, 304:

The total number of outliers from every features is: 48

The number of repeating outliers is: 5
Repeated outliers: [65, 66, 128, 154, 75]


        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
128  4.941642  9.087834   8.248791  4.955827          6.967909      1.098612
154  6.432940  4.007333   4.919981  4.317488          1.945910      2.079442
75   9.923192  7.036148   1.098612  8.390949          1.098612      6.882437



The shape of data without outliers is: (398, 6)
```

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:

- There are five data points considered outliers for more than one feature [65, 66, 128, 154, 75].
- First, outliers are nuisance in data only add abnormalities, should not be allowed and is extremely important in the data preprocessing. The presence of outliers can often skew results which take into consideration these data points.
- All the outliers that are outside the acceptable range (1.5 * IQR) should be removed fom data set to prevent them from having an outsized skewing effect on the analysis of the rest of the data. There are five outliers which are repeated in more than one feature. This may create another unwanted cluster also, if parameters are set favourable. Let's say we choose K-Means cluster as our model with number of clusters as total number of features. It may try to elongate the cluster in order to include the outlier data points causing wrong prediction or may end up creating another seperate clusters for them. Therefore they should be removed otherwise might fail forming clusters of similar customers.

** However outliers are not always bad to all sets of data. They sometime may contain necessary information which other normal data points can never provide. For example, in our data set, the data point indexed 65 shows Milk- 9.950323, Grocery- 10.732651 and Detergents- 10.095388. There might be chance that the customer being owner of big popular sweet restaurant. The restaurant utilises plenty of milk and grocery. Having large frequent number of customers dining may cause using a lot of detergents.

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

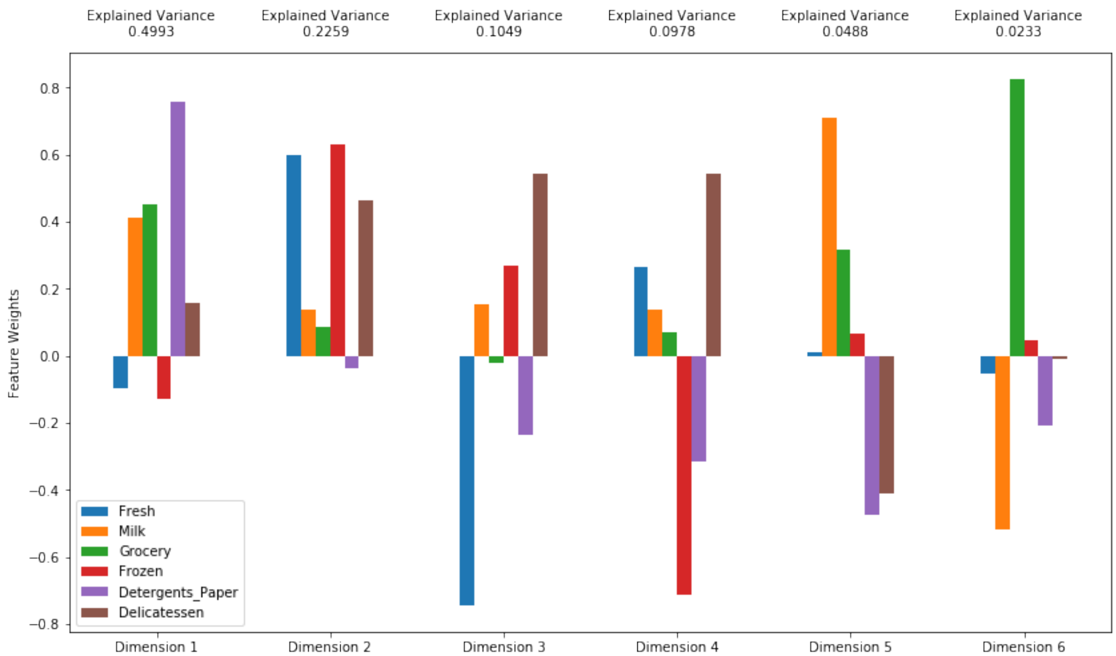
Now that the data has been scaled to a more normal distribution and has had any necessary outliers removed, we can now apply PCA to the `good_data` to discover which dimensions about the data best maximize the variance of features involved. In addition to finding these dimensions, PCA will also report 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 [67]: 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).fit(good_data)
         # no of components is by default min(n_samples, n_features) which is already 6, n_featu

         # 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:

- The variance in the data explained in total by the first and second principal component is 0.7252.
- The variance in the data explained by the first four principal components is 0.9279.
- 1) The Dimension 1 has large positive weights for milk, grocey and detergents_paper. They weigh more than 50% of total weight variation. This represents that large number of customers buy these category of proucts from this whole sale shop. These customers spend less amount on other products whose weights are comparatively low like fresh, frozen (negative) and delicatessen (positive). So this dimension badly assist in categorising fresh and frozen products and need other dimension to assist. These customers are like super market category.

- 2) The Dimension 2 shows high weights for features fresh, frozen and delicatessen and weigh more than 50% of weight variation. This dimension adds up information gain for these features. Rest three features are having small gain. This could categorise street vendors.
- 3) The Dimention 3 shows customers who tend to spend more of delicatessen and less on other products of milk and frozen. The negative weight of feature fresh indicates that, this dimension completely fails to give information about it. This dimension categorises customer having restaurants serving fast food.
- 4) The Dimension 4 show customers spending more on delicatessen, moderately on fresh products and very less on milk and grocery. This dimension excludes customers spending more on frozen (negative weight) products or need other dimension to back up. This indicates customers running small vegetable store.

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 [68]: # 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       1.8820       0.4617       0.2764       0.1055       0.0958
1      -0.9408      -0.1839      -0.8338      -0.0536      -0.3116
2       2.7381       0.2866      -0.5994       0.5811       0.0767

   Dimension 6
0      -0.2093
1       0.6337
2       0.0216
```

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

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

         # 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 [70]: # 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	1.8820	0.4617
1	-0.9408	-0.1839
2	2.7381	0.2866

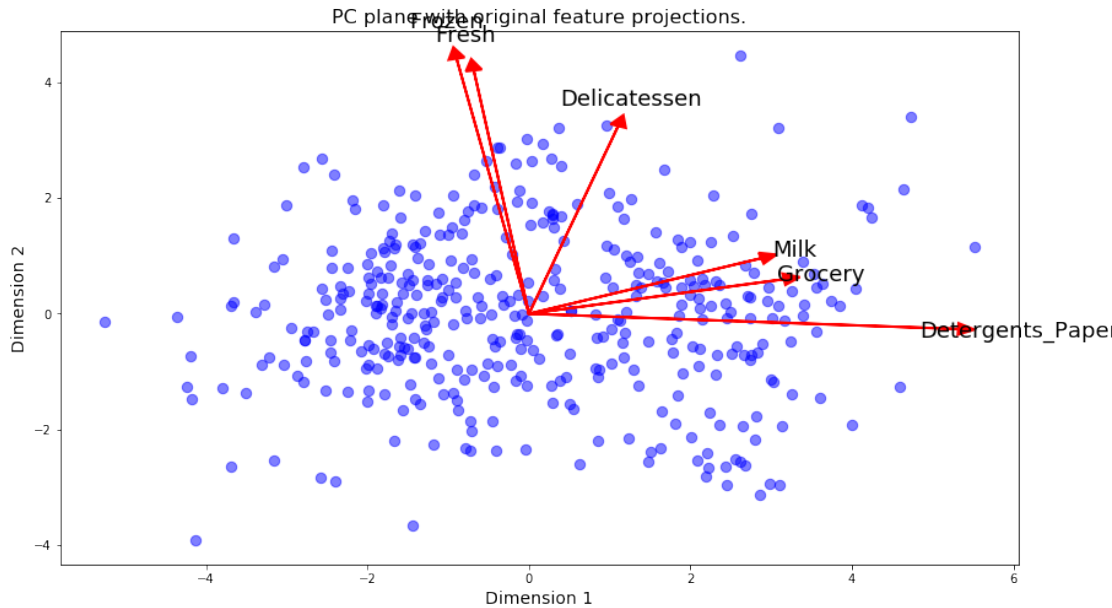
1.7 Visualizing a Biplot

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

```
Out[71]: <matplotlib.axes._subplots.AxesSubplot at 0x7f666abdcdd8>
```



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?

Answer The biplot shows that, original features Detergent_Paper and Grocery are most strongly coorelated with first component. The original features Fresh and Frozen are associated with the second component. These observation agree with the pca_results.

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:

- Advantages of K-Means clustering - It is easy to implement. In practice, the k-means algorithm is very fast (one of the fastest clustering algorithms available). That's why it can be useful to restart it several times. Running a dimensionality reduction algorithm such as PCA prior to k-means clustering can speed up the computations. Given enough time, K-means will always converge, however this may be to a local minimum.

- Advantages of Gaussian Mixture clustering - GMM is a lot more flexible in terms of cluster covariance. k-means is actually a special case of GMM in which each cluster's covariance along all dimensions approaches 0. This implies that a point will get assigned only to the cluster closest to it. With GMM, each cluster can have unconstrained covariance structure. It is the fastest algorithm for learning mixture models.

- For our wholesale customer data set, I intend to use GMM clustering because here customers do not distinctly fall on single category. They have mixed relationship with varity of features combination. GMM allows for mixed membership of points to clusters. In kmeans, a point belongs to one and only one cluster, whereas in GMM a point belongs to each cluster to a different degree. This degree is based on the probability of the point being generated from each cluster's (multivariate) normal distribution, with cluster center as the distribution's mean and cluster covariance as its covariance.

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 [72]:
```
from sklearn.mixture import GaussianMixture
from sklearn.metrics import silhouette_score
# TODO: Apply your clustering algorithm of choice to the reduced data
clusterer = GaussianMixture(n_components = 2, random_state=42).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)

print(score)
```

```
0.447411995571
```

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:

- I tried with 2-8 number of clusters.

  No of clusters: 2, Score: 0.447411995571

  No of clusters: 3, Score: 0.361193625039

  No of clusters: 4, Score: 0.318253457403

  No of clusters: 5, Score: 0.313056565177

  No of clusters: 6, Score: 0.340603716382

  No of clusters: 7, Score: 0.329660781949

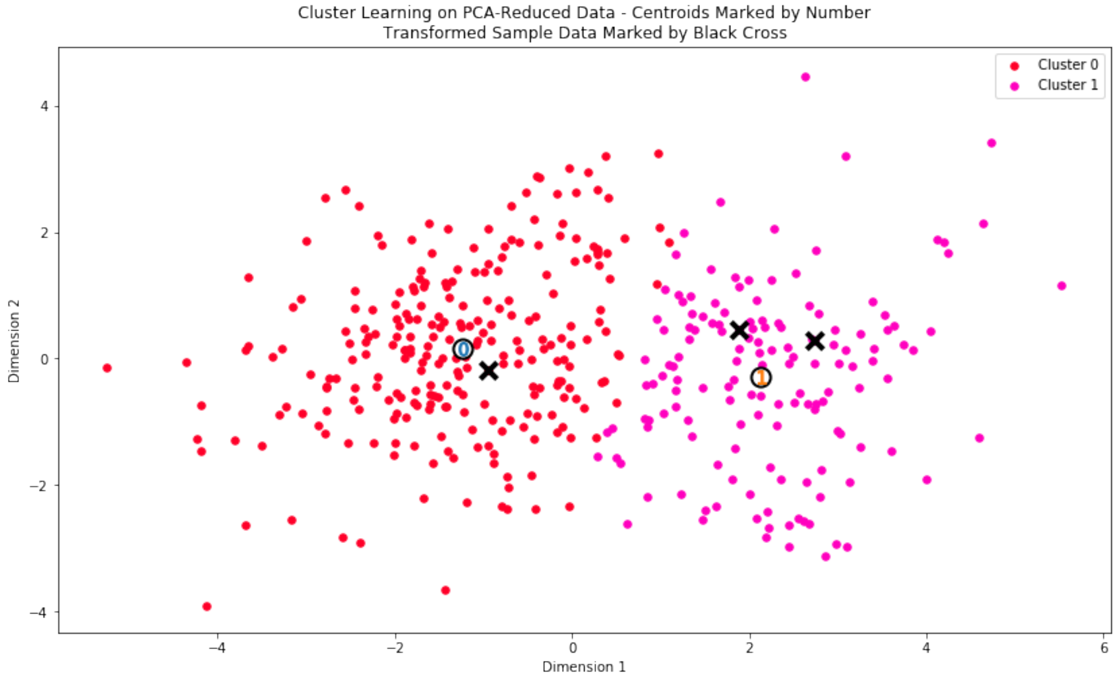
  No of clusters: 8, Score: 0.329122067795

- Out of all the experiment with number of clusters, the silhouette score is with 2 number of 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 [73]: # 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 [74]: # 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  9468.0  2067.0   2624.0  2196.0             343.0         799.0
Segment 1  5174.0  7776.0  11581.0  1068.0            4536.0        1101.0
```

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:

1) Segment 0: Comparing to mean values of each features of original data set, this customer spends very less on all product categories. All the purchase made comes around that of 50% of customers. This seems to be a general family person fulfilling his/her daily needs.

2) Segment 1: This customers shows symptoms of being a general grocery store or can say a super market. The purchase made on all the product categories is quite bigger than average of its respective category, except fresh products. Availibily of all kinds of products, gives the intution of it being a super market or grocey store.

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

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

Answer:
Here, we have made our model to classify all the customers into only two categories. We make categories as one being among (`Segment 1`) `retail stores, super markets, grocery stores` (all these sell products to be used by others). On the other hand, second category being customers under `Segment 0` who directly consume all products after purchase (for example, `coffee shops, family person, any small food vendors, restaurants` etc).

- `Data Index 1 = Sample point 0`: Earlier, I predicted it to be a sweet restaurant but our model categorise it under segment 1 calling it a some kind of store.
- `Data Index 11 = Sample point 1`: Correctly predicted it to be a street vendor which use to consume all of its item on daily basis, falls under segment 0.
- `Data Index 111 = Sample point 2`: Predict it to be a super market or any grocery store, falls correctly under segment 1.

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:

Considering the above two segments, we can intuitively choose segment 1 to experiment this delivery frequency changes. This is so because, retail or grocery stores need to keep sufficient amount of all the product in order to meet adverse demand of the market. The super markets even has big stores and cold storage too, just for these kind of sudden adverse demand in the market. So they can easily deal with lower frequency of supply. On the other hand, small vendors, restaurants, shops etc do not posses these facilities and storing is costly too for them.

But to proceed algorithmically, we can take small sample of data points close to the centres of clusters to experiment with. We divide those samples into two and make delivery scheme changes into 1st sub sample data points and observe their changes (response from those customers) in comparison to response of 2nd sub sample having same old delivery scheme. The responses from customers can be either by email responses, survey, votings etc. On getting favourable responses from customers we can choose to either proceed with new scheme or not.

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 have our already trained unsupervised model GMM. We can just feed our new data points to it and will result respective cluster or customer segment for them.

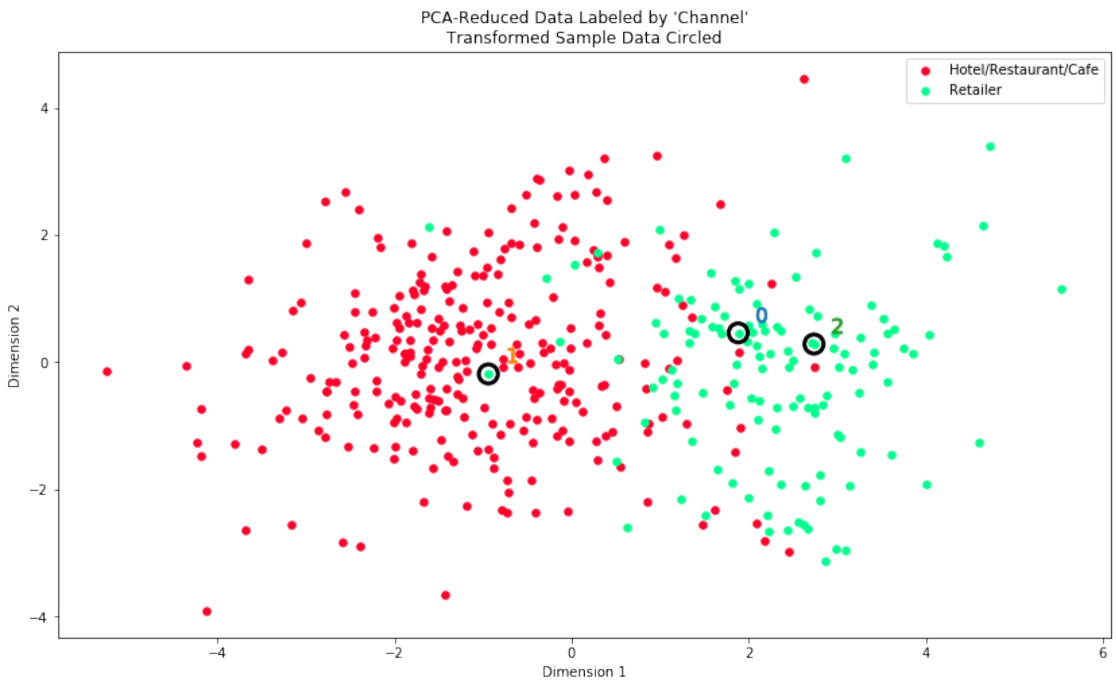
If we need to proceed with supervised learning, we have our labels achieved as customer segments. We just need a supervised learning model, let's say Decision Tree Classifier and train it with old data set with target as customer segments. Once fitted, we check its metrics score and judge it. Having good score we can proceed to feed our new data points and get customer segments for them.

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 [76]:
```
# 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:

We trained our model with two clusters, and this new data set has same number of channels, so they fairly align together. Although there are number of data points which are misclassified. Few data points in both clusters happen to be categorised into another cluster. They are wrongly labelled. Also there seems no clear boundary between two clusters. The segment 0 is channel 'Hotels/Restaurants/Cafes' and segment 1 is channel 'Retailer'. I accept that this model has done quite a good job for categorising customers and can be used in business.

> **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.