customer_segments

August 24, 2017

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 [1]: # Import libraries necessary for this project
        import numpy as np
        import pandas as pd
        from IPython.display import display # Allows the use of display() for DataFrames
        import matplotlib.pyplot as plt
        import seaborn as sns
        sns.set_style('darkgrid')
        sns.set_context('notebook')
        # 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(*da
        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 [2]: # 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 [3]: # TODO: Select three indices of your choice you wish to sample from the dataset
        indices = [10, 150, 350]

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

```
Chosen samples of wholesale customers dataset:


   Fresh  Milk  Grocery  Frozen  Detergents_Paper  Delicatessen
0   3366  5403    12974    4400              5977          1744
1  16225  1825     1765     853               170          1067
2   3521  1099     1997    1796               173           995
```

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, and retailers, among many others. Avoid using names for establishments, such as saying *"McDonalds"* when describing a sample customer as a restaurant.

Customer 1: spendng amount is close to 75% quantile in all product category, which may indicate that this customer could be a retailer.

Customer 2: this customer has little spending in all categories except moderate amount of Deli and high ammount of fresh product. This pattern may indicate that this costumer is a health conscience cafe or resturant.

Customer 3: has little spending amount in all categories except close to median amount in frozen food category. This could be spending pattern for cheap low quality resturant or cafe.

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

        # TODO: Split the data into training and testing sets using the given feature as the tar
        from sklearn.model_selection import train_test_split
        X_train, X_test, y_train, y_test = train_test_split(new_data,
                                                             data.Fresh,
                                                             test_size=0.25,
                                                             random_state=1)

        # TODO: Create a decision tree regressor and fit it to the training set
        from sklearn.tree import DecisionTreeRegressor
        from sklearn.model_selection import GridSearchCV

        regressor = DecisionTreeRegressor(random_state=1, )
        grid_search = GridSearchCV(regressor,
                                   cv=10,
                                  param_grid={'max_depth': range(2, 20),
                                              'criterion': ['mse', 'mae', 'friedman_mse'],
                                              'splitter': ['random', 'best']})

        grid_search.fit(X_train, y_train)
        preds = grid_search.predict(X_test)
        # TODO: Report the score of the prediction using the testing set
        from sklearn.metrics import r2_score
        score = r2_score(y_test, preds)
        print(score)
```

```
-0.0638573353331
```

1.4.4 Question 2

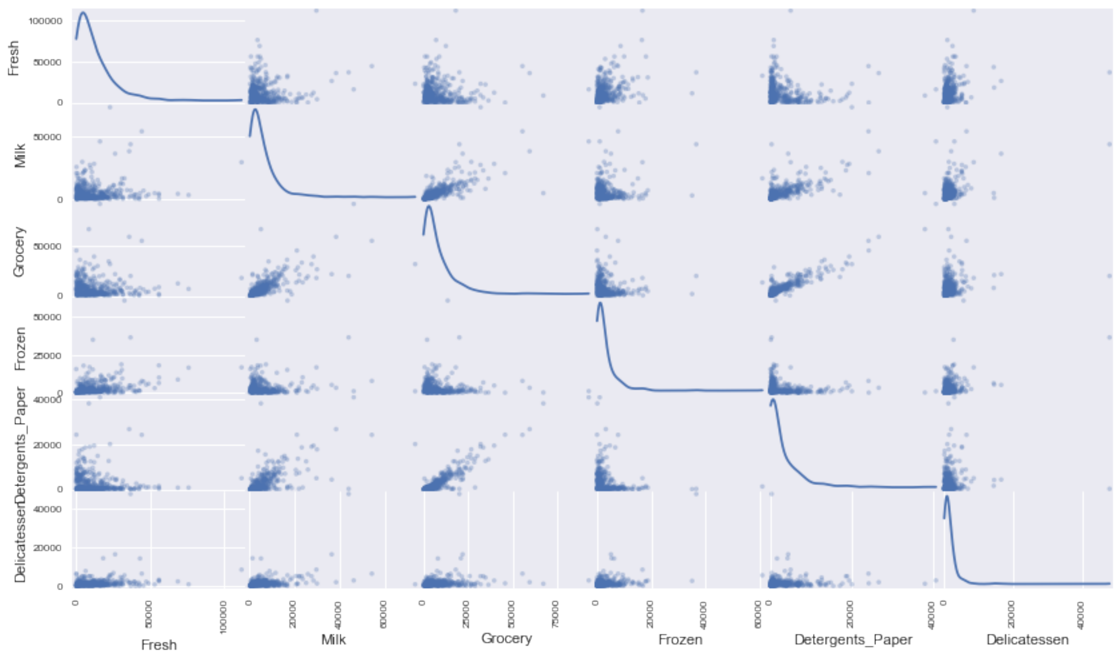
Which feature did you attempt to predict? What was the reported prediction score? Is this feature necessary for identifying customers' spending habits?
Hint: The coefficient of determination, `R^2`, is scored between 0 and 1, with 1 being a perfect fit. A negative `R^2` implies the model fails to fit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

The feature I choose to predict is Fresh and the coefficient of determination was -0.064. The negative sign of R^2 indicates the mean of the data is better than predicted values from the Decision Tree Regression.

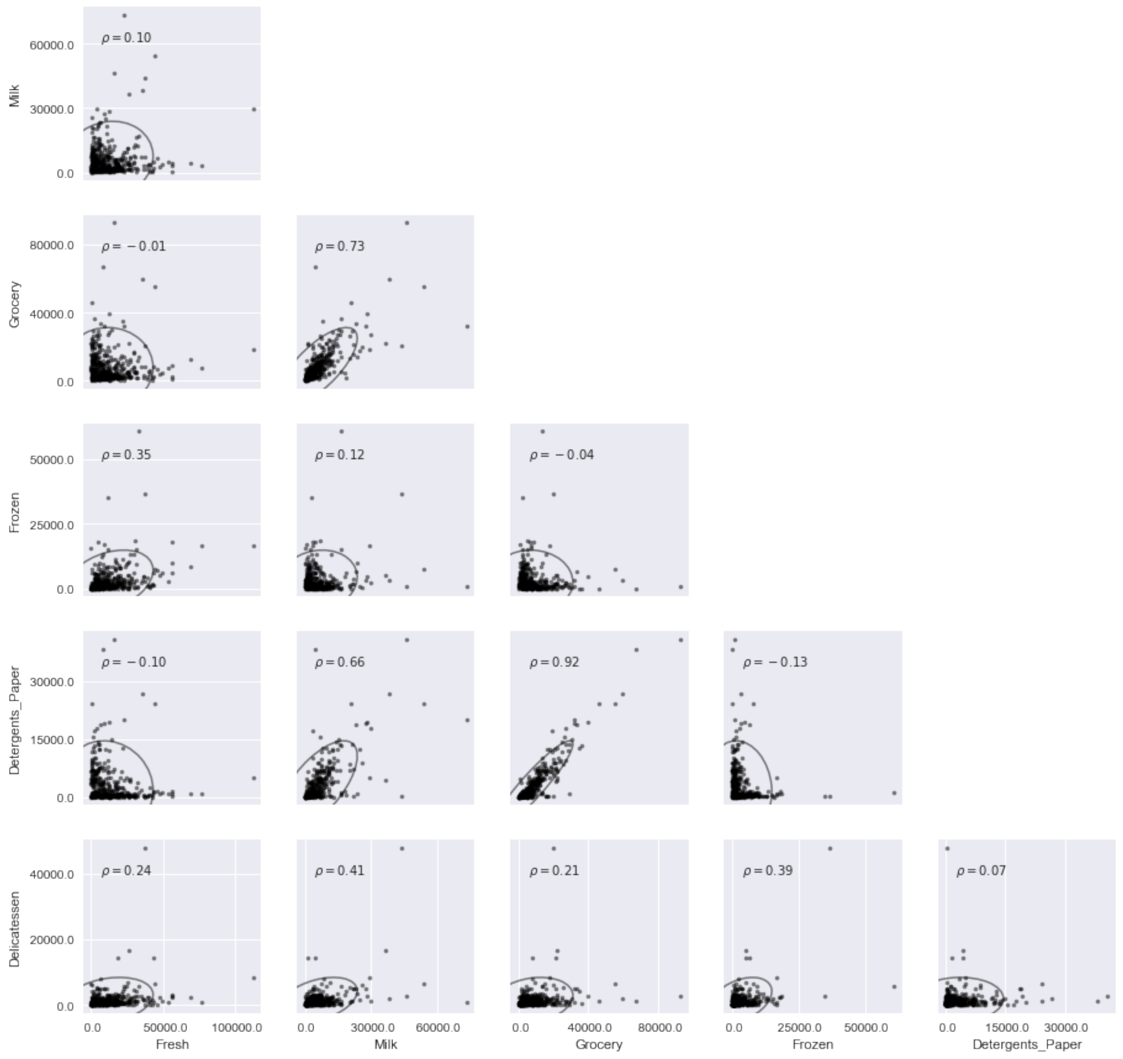
1.4.5 Visualize Feature Distributions

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 [5]: # 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 [6]: from statsmodels.graphics.plot_grids import scatter_ellipse
        fig = plt.figure(figsize=(15, 15))
        fig = scatter_ellipse(data.as_matrix(), varnames=data.columns, add_titles=0, fig=fig, le
```



1.4.6 Question 3

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

The highest pairwise correlations exist between Grocery-Detergent paper (0.92), Milk-Detergent Paper (0.66) and Milk-Grocery (0.73). The correlation plot confirms our expectation that varible Fresh has very small correlation with other predictors and can add more information compared to highly correlated predictor such as Grocery or Detergent paper. Predictors are highly skewed with many outliers. The correlation plot obtained from statsmodels packages provides confidence ellipses (95% confidence) which helps us study the pairwise correlation while we have many 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

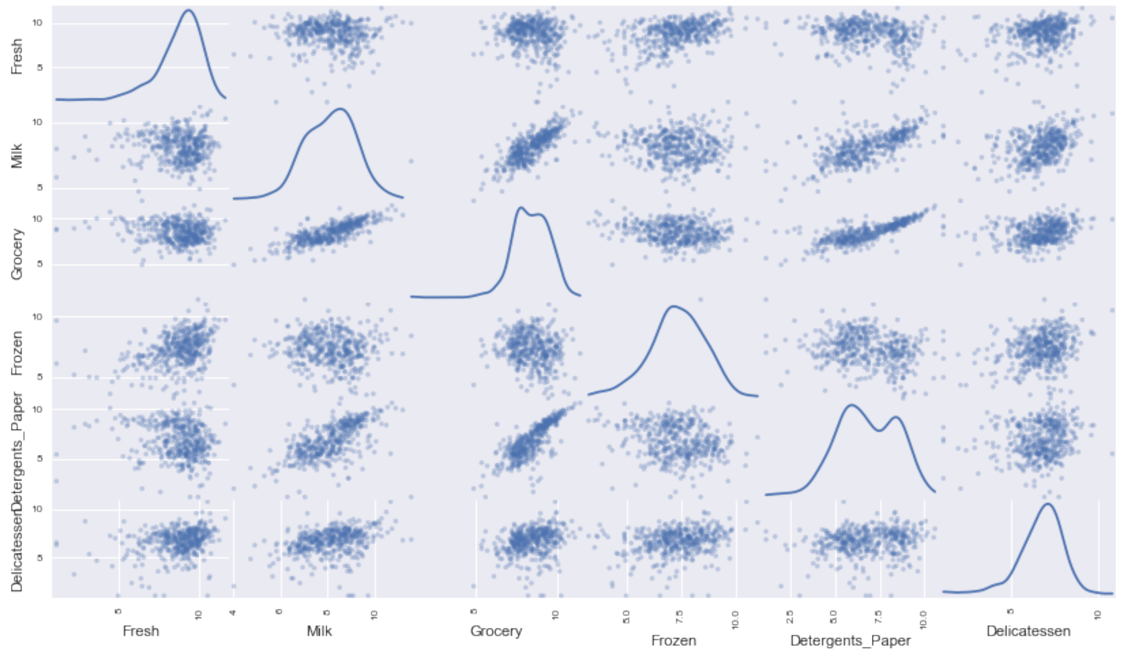
If data is not normally distributed, especially if the mean and median vary significantly (indicating a large skew), it is most often appropriate to apply a non-linear scaling — particularly for financial data. One way to achieve this scaling is by using a Box-Cox test, which calculates the best power 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 [7]: # TODO: Scale the data using the natural logarithm
        log_data = np.log(data)

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

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



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

```
      Fresh      Milk   Grocery    Frozen  Detergents_Paper  Delicatessen
0  8.121480  8.594710  9.470703  8.389360          8.695674      7.463937
1  9.694309  7.509335  7.475906  6.748760          5.135798      6.972606
2  8.166500  7.002156  7.599401  7.493317          5.153292      6.902743
```

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 [9]: data.index
```

```
Out[9]: RangeIndex(start=0, stop=440, step=1)
```

```
In [10]: # For each feature find the data points with extreme high or low values
         from collections import Counter

         duplicate = Counter()

         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)
    outlier = log_data[~((log_data[feature] >= Q1 - step) & (log_data[feature] <= Q3 +
    display(outlier)
    for indx in outlier.index:
        duplicate[indx] += 1

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

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

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


        Fresh       Milk    Grocery    Frozen  Detergents_Paper  Delicatessen
65   4.442651   9.950323  10.732651  3.583519         10.095388      7.260523
66   2.197225   7.335634   8.911530  5.164786          8.151333      3.295837
81   5.389072   9.163249   9.575192  5.645447          8.964184      5.049856
95   1.098612   7.979339   8.740657  6.086775          5.407172      6.563856
96   3.135494   7.869402   9.001839  4.976734          8.262043      5.379897
128  4.941642   9.087834   8.248791  4.955827          6.967909      1.098612
171  5.298317  10.160530   9.894245  6.478510          9.079434      8.740337
193  5.192957   8.156223   9.917982  6.865891          8.633731      6.501290
218  2.890372   8.923191   9.629380  7.158514          8.475746      8.759669
304  5.081404   8.917311  10.117510  6.424869          9.374413      7.787382
305  5.493061   9.468001   9.088399  6.683361          8.271037      5.351858
338  1.098612   5.808142   8.856661  9.655090          2.708050      6.309918
353  4.762174   8.742574   9.961898  5.429346          9.069007      7.013016
355  5.247024   6.588926   7.606885  5.501258          5.214936      4.844187
357  3.610918   7.150701  10.011086  4.919981          8.816853      4.700480
412  4.574711   8.190077   9.425452  4.584967          7.996317      4.127134


Data points considered outliers for the feature 'Milk':


         Fresh       Milk    Grocery    Frozen  Detergents_Paper  Delicatessen
86   10.039983  11.205013  10.377047  6.894670          9.906981      6.805723
98    6.220590   4.718499   6.656727  6.796824          4.025352      4.882802
154   6.432940   4.007333   4.919981  4.317488          1.945910      2.079442
```

```
356  10.029503   4.897840   5.384495  8.057377          2.197225      6.306275


Data points considered outliers for the feature 'Grocery':


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


Data points considered outliers for the feature 'Frozen':


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


Data points considered outliers for the feature 'Detergents_Paper':


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


Data points considered outliers for the feature 'Delicatessen':


         Fresh       Milk    Grocery     Frozen  Detergents_Paper  \
66    2.197225   7.335634   8.911530   5.164786          8.151333
109   7.248504   9.724899  10.274568   6.511745          6.728629
128   4.941642   9.087834   8.248791   4.955827          6.967909
137   8.034955   8.997147   9.021840   6.493754          6.580639
142  10.519646   8.875147   9.018332   8.004700          2.995732
154   6.432940   4.007333   4.919981   4.317488          1.945910
183  10.514529  10.690808   9.911952  10.505999          5.476464
184   5.789960   6.822197   8.457443   4.304065          5.811141
187   7.798933   8.987447   9.192075   8.743372          8.148735
203   6.368187   6.529419   7.703459   6.150603          6.860664
```

```
233   6.871091   8.513988   8.106515   6.842683          6.013715
285  10.602965   6.461468   8.188689   6.948897          6.077642
289  10.663966   5.655992   6.154858   7.235619          3.465736
343   7.431892   8.848509  10.177932   7.283448          9.646593

     Delicatessen
66       3.295837
109      1.098612
128      1.098612
137      3.583519
142      1.098612
154      2.079442
183     10.777768
184      2.397895
187      1.098612
203      2.890372
233      1.945910
285      2.890372
289      3.091042
343      3.610918
```

```
In [11]: # repeated outliers
         print([indx for indx, value in duplicate.iteritems() if value > 1])
```

```
[128, 154, 65, 66, 75]
```

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.

Points 128, 154, 65, 66 and 75 are outliers in more than one feature. The data points should be removed if there is confidence in that outlying points are in fact erroneous. The analysis can be repeated later with outlying points remove to determine their effect on performance of the model.

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

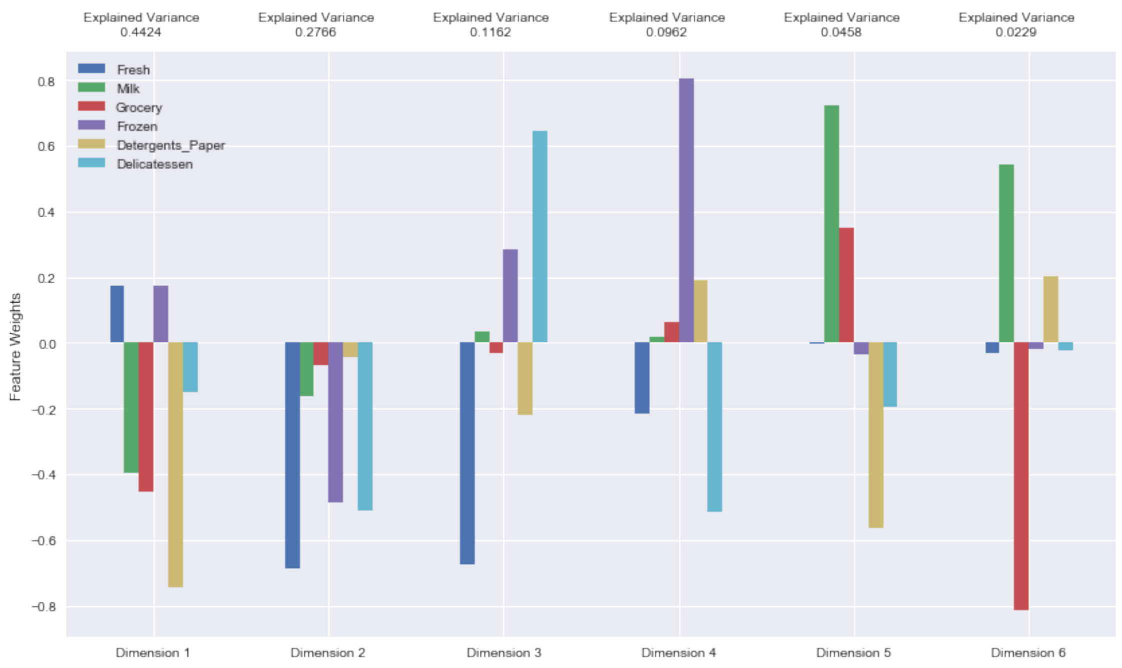
Now that the data has been scaled to a more normal distribution and has had any necessary outliers removed, we can now apply PCA to the `good_data` to discover which dimensions about the data best maximize the variance of features involved. In addition to finding these dimensions, PCA will also report 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 [12]: # TODO: Apply PCA by fitting the good data with the same number of dimensions as featur
         from sklearn.decomposition import PCA
         pca = PCA(n_components=good_data.shape[1], random_state=1, whiten=0)
         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? What about the first four principal components? Using the visualization provided above, discuss what the first four dimensions best represent in terms of customer spending.*

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

The first and second principle components can explain 44.2% and 27.7% of variation in the data respectively which add up to 71.9%.

The first four princple components expailn 93.13% of variation in customer spending data.

- The 1st principle component dominated by Detergent-Paper, Grocery and Milk.
- The 2nd principle component is dominated by Fresh, Frozen and Delicatessen.
- The 3rd principle compontent maily show the difference between Fresh and the two variables Frozen and Delicatessen.
- The 4th principle component shows the decrease annd increase in Delicattessen and Frozen variables.

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 [13]: # 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      -2.1162      -0.7488       0.8007       1.0355      -0.5710
1       1.9364      -0.3120      -0.2373      -1.1971       0.1116
2       1.9406       0.4803       0.9341      -0.2318      -0.2337

   Dimension 6
0      -0.2135
1       0.0938
2      -0.2453
```

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 [14]: # TODO: Apply PCA by fitting the good data with only two dimensions
         from sklearn.decomposition import PCA
         pca = PCA(n_components=2, random_state=1)
         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 [15]: # 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      -2.1162      -0.7488
1       1.9364      -0.3120
2       1.9406       0.4803
```

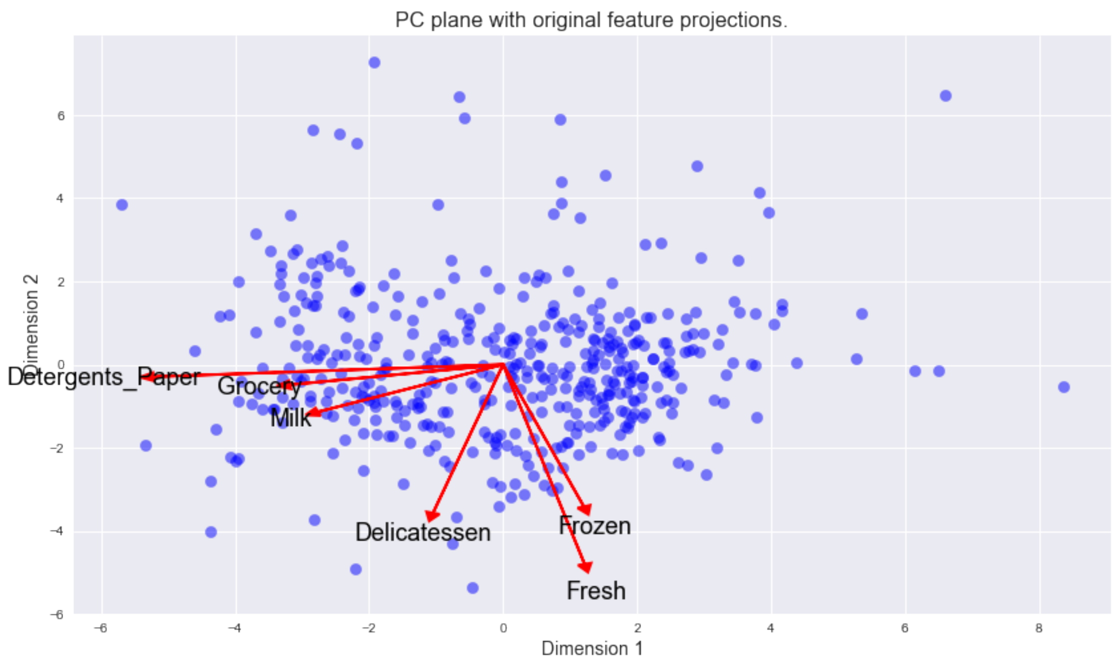
1.7 Visualizing a Biplot

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

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6343a09f50>
```



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?

k-means: is hard clustering algorithm which only assign each object to one cluster. In k-means clustering the number of is decided at the beginning and objects iteratively assign to k clusters then the cluster re-evaluated iteratively until there's no change or we reach some predefined thereshhold. The k-means algorithm is fast and but it's sensative to the initialization of center points and outliers.

Gaussian Mixture Models: is soft clustering algorithm which assign degree to which each object belong to a cluster. Gaussian mixtures model is also sensative to initialization of center points.

Since the data in the above plot is easily distinguishable, as soft clustering algorithm such as Gausssian mixtures models is a better choice in our case.

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 [17]: # TODO: Apply your clustering algorithm of choice to the reduced data
         from sklearn.mixture import GaussianMixture
         from sklearn.metrics import silhouette_score
         center_list = []
         scores = []
         samples = []
         pred = []
         for k in range(2, 15):
             clusterer = GaussianMixture(n_components=k,
                                          random_state=1,
                                         covariance_type='spherical')
             clusterer.fit(reduced_data)
             # TODO: Predict the cluster for each data point
             preds = clusterer.predict(reduced_data)
             pred.append(preds)

             # TODO: Find the cluster centers
             center_list.append(clusterer.means_)

             # TODO: Predict the cluster for each transformed sample data point
             samples.append(clusterer.predict(pca_samples))
             # TODO: Calculate the mean silhouette coefficient for the number of clusters chosen
```

```
            scores.append(silhouette_score(reduced_data, preds))
        best_model_indx = np.argmax(scores)
        sample_preds = samples[best_model_indx]
        centers = center_list[best_model_indx]
        score = scores[best_model_indx]
        preds = pred[best_model_indx]
        display(pd.DataFrame({'k': range(2, 15),
                              'scores %': 100 * np.round(scores, 3)}))
```

```
     k  scores %
0    2      42.0
1    3      40.4
2    4      37.3
3    5      30.3
4    6      35.5
5    7      31.3
6    8      29.6
7    9      32.9
8   10      34.3
9   11      32.4
10  12      31.3
11  13      32.9
12  14      32.4
```

1.8.3 Question 7

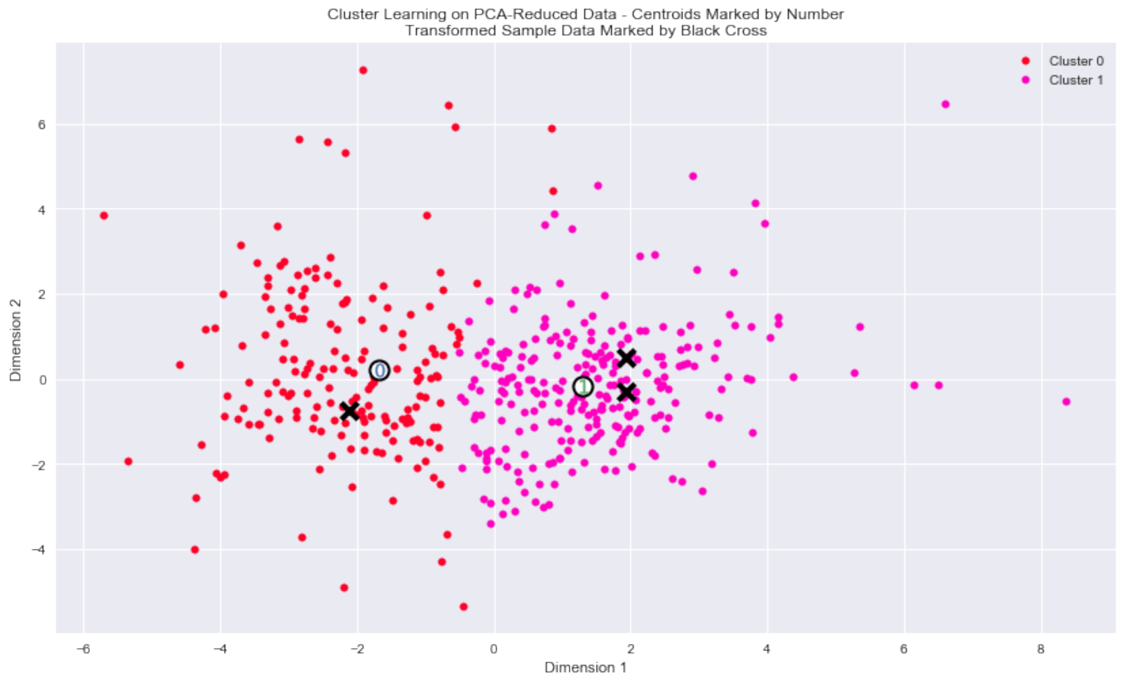
Report the silhouette score for several cluster numbers you tried. Of these, which number of clusters has the best silhouette score?

The model with 3 mixture components have the highest silhouette score.

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 [18]: # 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 [19]: # 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  4011.0  6314.0   9804.0  1003.0              3073.0          908.0
Segment 1  8662.0  2066.0   2593.0  2006.0               338.0          701.0
```

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. *What set of establishments could each of the customer segments represent?*
Hint: A customer who is assigned to `'Cluster X'` should best identify with the establishments represented by the feature set of `'Segment X'`.

Segment 1 has higher spending amount on fresh and frozen products while segment 0 has very high amount of detergent paper and groceries. This indicates that segment 1 is a representative of a cafe or resturant and segment 0 is representative of a retail stroe.

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

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

Samples 0 belong to cluster 0 which is representative of retailers and samples 1, 2 belong to cluster 1 which is represantative of a resturant or a cafe. These predictions are consistent with our previous expectations.

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?

Earlier we found that the main differences in the two clusters are the amount of spending of fresh and frozen product in resturants and cafes and non-perishable items such as detergent paper. It make sense to assume that customer with higher spending on fresh and frozen food would benefit from increasing the delivery frequency. It is also possible that retailers with small storage capacity will benefit from increased delivary frequency. The company can use A/B testing by randomly selecting a subset of each segment and offer the 3 day delivery service to them. If the new delivary service has positive and statistically signifcant effect on any of these two segment the company can change the delivery policy for that segment.

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?

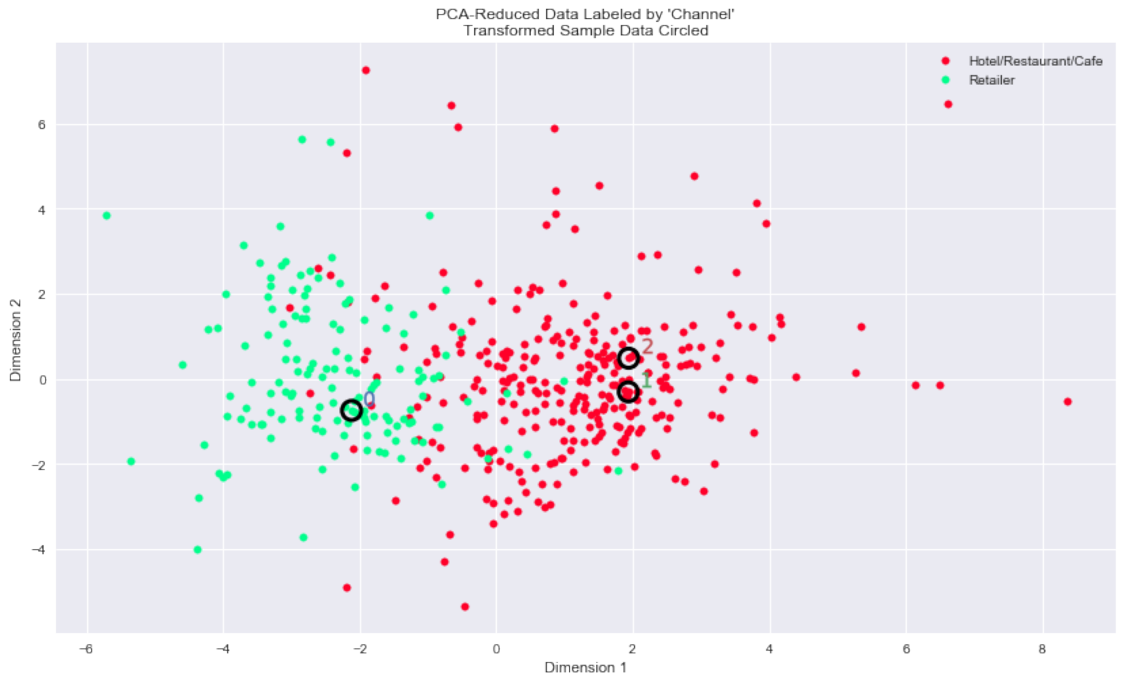
The target variable would be the assigned label from clustering process.

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 [26]: # 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?

```
In [62]: from __future__ import division

         data = pd.read_csv("customers.csv")
         accuracy = sum(np.equal(data.Channel > 1 , preds < 1)) / data.shape[0]
         print("accuracy: {} %").format(accuracy * 100)
```

```
accuracy: 88.4090909091 %
```

The consistancy between clustering result and the real data is high (88.4%). The are some extream points to in the left and right that could be classified as purley retailers or Hotels/Restaurants/Cafes but there are some points that are quiet mixed in the middle. The sample points we earlier are still in the same clusters.

> **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.