Machine Learning Engineer Nanodegree

Unsupervised Learning

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.

Getting Started

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

The dataset for this project can be found on the [UCI Machine Learning Repository (https://archive.ics.uci.edu/ml/datasets/Wholesale+customers)](https://archive.ics.uci.edu/ml/datasets/Wholesale+customers). For the purposes of this project, the features `'Channel'` and `'Region'` will be excluded in the analysis — with focus instead on the six product categories recorded for customers.

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

In [1]:

```
# Import libraries necessary for this project
import numpy as np
import pandas as pd
from IPython.display import display # Allows the use of display() for DataFram
es

# 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(*data.shape))
except:
    print("Dataset could not be loaded. Is the dataset missing?")
```

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

Data Exploration

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

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

In [2]:

```
# Display a description of the dataset
display(data.describe())
```

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

Implementation: Selecting Samples

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

In [3]:

```
# TODO: Select three indices of your choice you wish to sample from the datase
t
indices = [2, 61, 311]

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

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

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	6353	8808	7684	2405	3516	7844
1	35942	38369	59598	3254	26701	2017
2	29635	2335	8280	3046	371	117

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: 7951.3
- 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:

- The first customer (indice=2) purchased more stuffs than average in Milk, Detergents_Paper, and Delicatessen categories. It may be a cafe that needs more milk for selling beverage like latte, more delicatessen for selling snacks and more detergents paper for customers wiping hands after they enjoying snacks.
- The second customer (indice=61) purchased much more stuffs than average in Fresh, Milk, Grocery and Detergents_Paper categories. It could probably be a wholesale retailer that purchased such numerous stuffs.
- The third customer (indice=311) purchased much more stuffs than average in Fresh category, a bit more stuffs than average in Grocery category and less stuffs than average in Milk, Detergents_Paper and Delicatessen categories. It could be a fresh supermarket that sells lots of meats and fishes and some groceries.

Implementation: Feature Relevance

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

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

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

In [4]:

```
# TODO: Make a copy of the DataFrame, using the 'drop' function to drop the gi
ven feature
new_data = data.drop("Detergents_Paper", axis=1)
#print(new_data.head())

# TODO: Split the data into training and testing sets(0.25) using the given fe
ature as the target
# Set a random state.
from sklearn.cross_validation import train_test_split
X_train, X_test, y_train, y_test = train_test_split(new_data, data["Detergents
_Paper"], test_size=0.25, random_state=12)

# TODO: Create a decision tree regressor and fit it to the training set
from sklearn.tree import DecisionTreeRegressor
regressor = DecisionTreeRegressor(random_state=7)
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("Prediction score : ",score)
```

```
Prediction score :  0.777421877012

/Users/RAYMOND/miniconda3/lib/python3.5/site-packages/sklearn/cros
s_validation.py:41: DeprecationWarning: This module was deprecated
in version 0.18 in favor of the model_selection module into which
all the refactored classes and functions are moved. Also note that
the interface of the new CV iterators are different from that of t
his module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

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 chose Detergents_Paper to predict and the reported prediction score is about 0.7774. Since the scoring metric is R^2, values between 0 and 1 measures how good the model fits and value that near 1 means more perfect the model fit the data. This high score means high correlation between Detergents_Paper and other features, i.e. we can obtain most information of Detergents_Paper based on other features. Therefore, Detergents_Paper isn't an necessary feature to identify customers' spending habits.

Visualize Feature Distributions

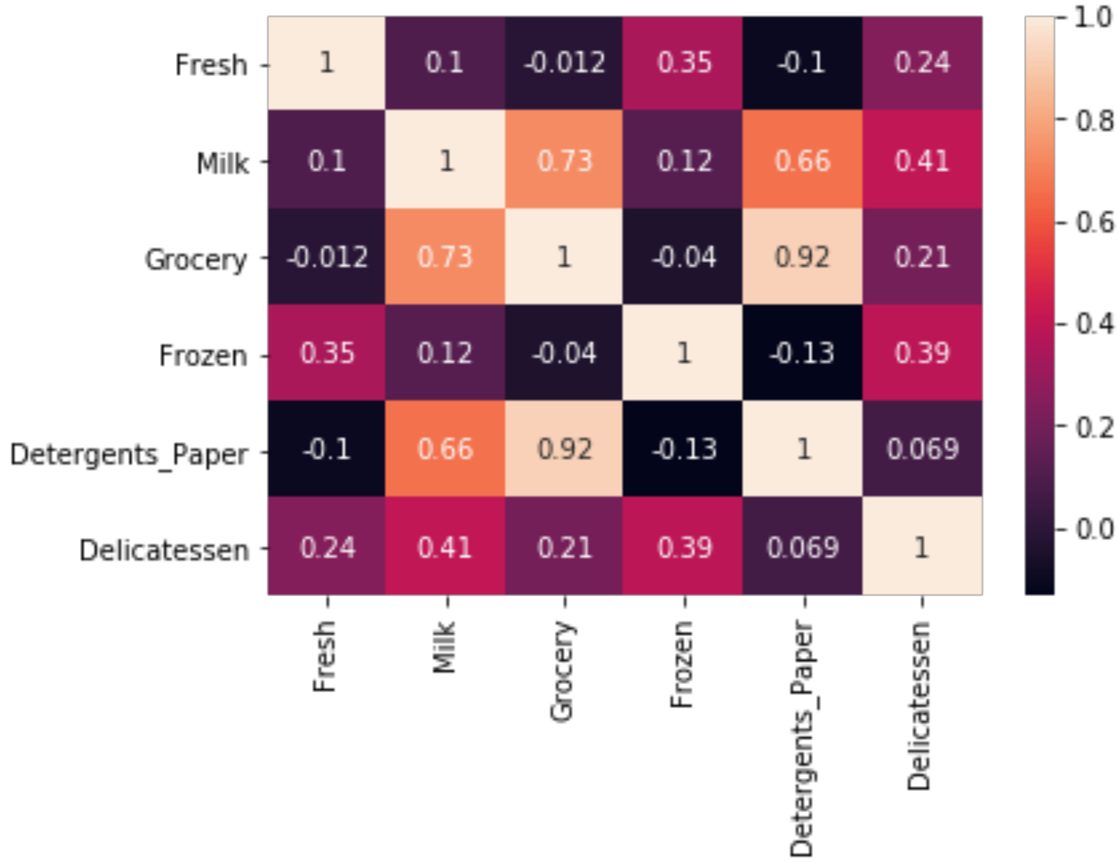
To get a better understanding of the dataset, we can construct a scatter matrix of each of the six product features present in the data. If you found that the feature you attempted to predict above is relevant for identifying a specific customer, then the scatter matrix below may not show any correlation 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.

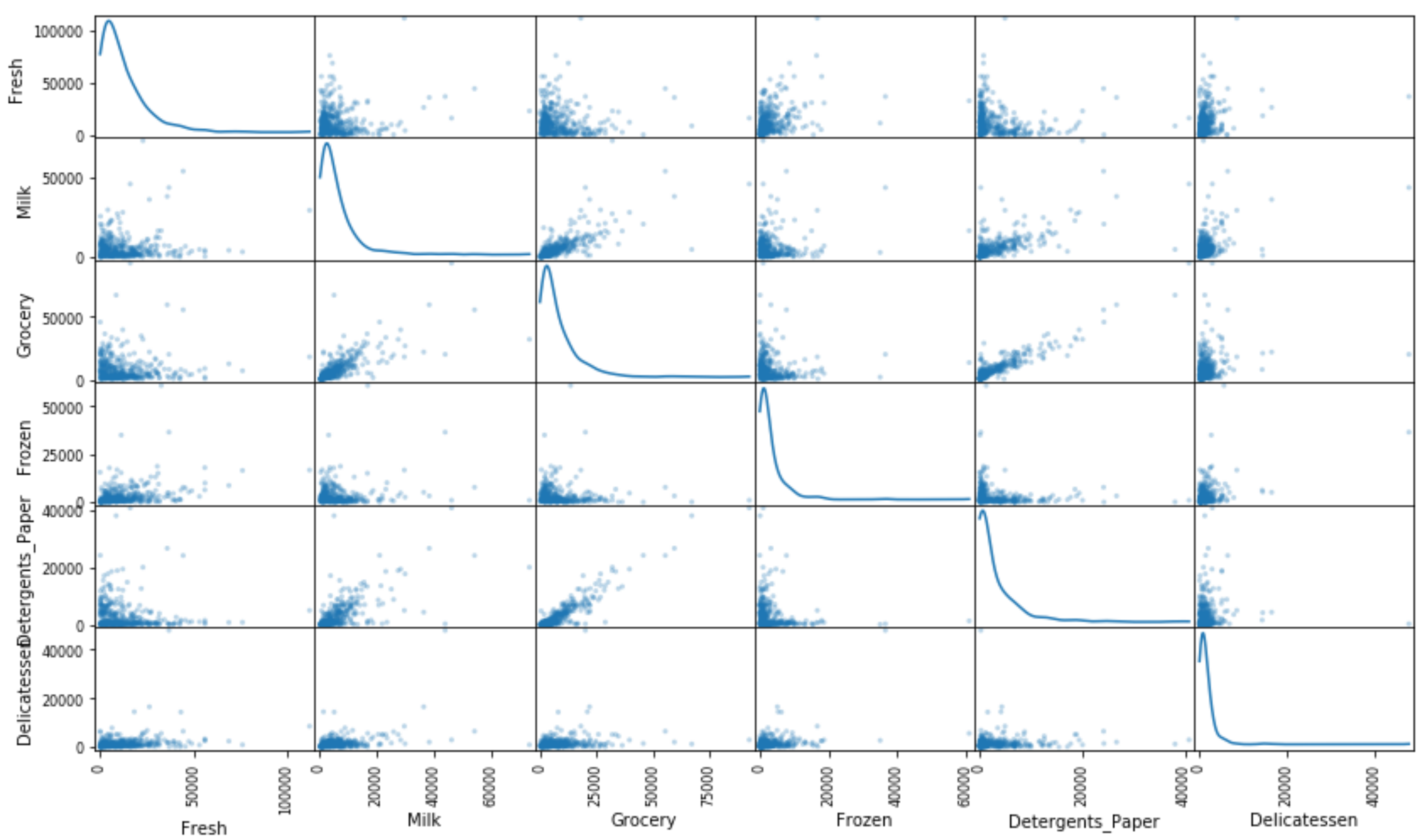
In [5]:

```
from seaborn import heatmap
heatmap(data.corr(), annot=True)

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

```
/Users/RAYMOND/miniconda3/lib/python3.5/site-packages/ipykernel_la
uncher.py:5: FutureWarning: pandas.scatter_matrix is deprecated, u
se pandas.plotting.scatter_matrix instead
  """
```





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() (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.corr.html) to get the feature correlations and then visualize them using a heatmap (http://seaborn.pydata.org/generated/seaborn.heatmap.html)(the data that would be fed into the heatmap would be the correlation values, for eg: `data.corr()`) to gain further insight.

Answer:

- These data aren't normally distributed, and most data densely lie below 10000. On the other hand, there're outliers much farer than major data distribution region, which is not a good sign for applying machine learning model.
- Scatter plot of Grocery and Detergents_Paper is distributed like a straight line. It indicates high correlation between Grocery and Detergents_Paper.
- Scatter plot of Grocery and Milk also shows a straight line distribution, which means high correlation between Grocery and Milk.
- It confirms my suspicion that Detergents_Paper has high correlation with other features and now we know among of them, Grocery and Milk are most correlated features.
- These data are right skew distributed. Most values lies below 10000 and they're unevenly distributed near the peak center.

Data Preprocessing

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

Implementation: Feature Scaling

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

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

- Assign a copy of the data to `log_data` after applying 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`.

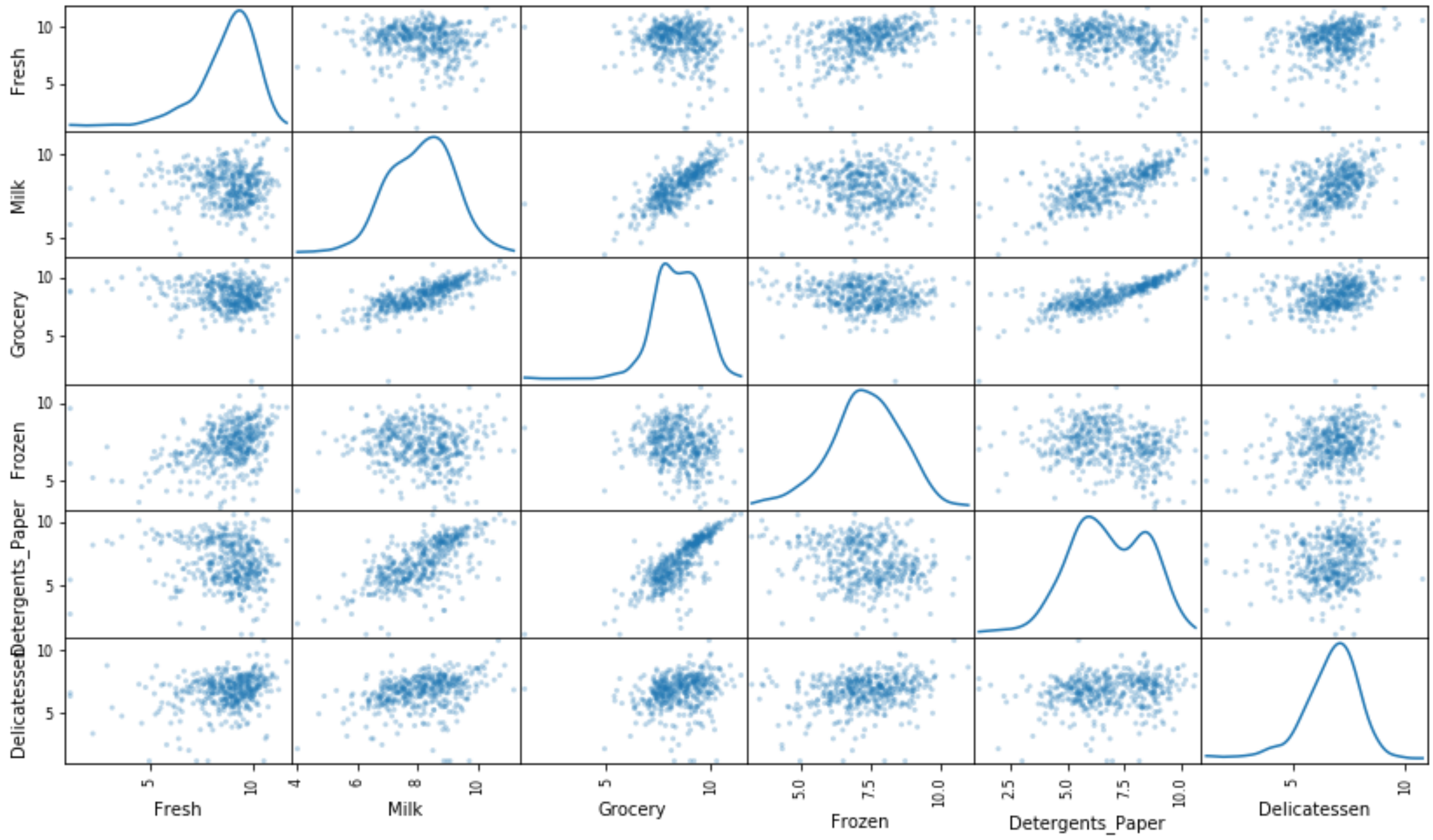
In [6]:

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

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

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

```
/Users/RAYMOND/miniconda3/lib/python3.5/site-packages/ipykernel_la
uncher.py:8: FutureWarning: pandas.scatter_matrix is deprecated, u
se pandas.plotting.scatter_matrix instead
```



Observation

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

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

In [7]:

```
# Display the log-transformed sample data
display(log_samples)
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	8.756682	9.083416	8.946896	7.785305	8.165079	8.967504
1	10.489662	10.555005	10.995377	8.087640	10.192456	7.609367
2	10.296711	7.755767	9.021598	8.021585	5.916202	4.762174

Implementation: Outlier Detection

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

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

- Assign the value of the 25th percentile for the given feature to `Q1`. Use `np.percentile` for this.
- Assign the value of the 75th percentile for the given feature to `Q3`. Again, use `np.percentile`.
- Assign the calculation of an outlier step for the given feature to `step`.
- Optionally remove data points from the dataset by adding indices to the `outliers` list.

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

In [8]:

```
outliers  = []
outliers_removed = []
duplicate_outliers = []

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

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

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

    # TODO: Use the interquartile range to calculate an outlier step (1.5 time
s the interquartile range)
    step = 1.5 * (Q3 - Q1)
    IQR3 = 3.0 * (Q3 - Q1)

    # Display the outliers
    print("Data points considered outliers for the feature '{}':".format(featu
re))
    display(log_data[~((log_data[feature] >= Q1 - step) & (log_data[feature] <
= Q3 + step))])

    feature_outliers = log_data[~((log_data[feature] >= Q1 - step) & (log_data
[feature] <= Q3 + step))]
    feature_outliers_removed = log_data[~((log_data[feature] >= Q1 - IQR3) & (
log_data[feature] <= Q3 + IQR3))]

    for i in feature_outliers.index :
        if i not in outliers :
            outliers.append(i)
        elif i not in duplicate_outliers :
            duplicate_outliers.append(i)

    for i in feature_outliers_removed.index :
        if i not in outliers_removed :
            outliers_removed.append(i)
    #print(outliers)


# OPTIONAL: Select the indices for data points you wish to remove
#outliers  = []
print("Outliers : " , outliers)
print("Outliers to be removed : " , outliers_removed)
print("Duplicate outliers : " , duplicate_outliers)

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

Data points considered outliers for the feature 'Fresh':

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

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

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

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

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

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

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

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

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

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

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

```
Outliers :  [65, 66, 81, 95, 96, 128, 171, 193, 218, 304, 305, 338
, 353, 355, 357, 412, 86, 98, 154, 356, 75, 38, 57, 145, 175, 264,
325, 420, 429, 439, 161, 109, 137, 142, 183, 184, 187, 203, 233, 2
85, 289, 343]
Outliers to be removed :  [66, 95, 218, 338, 75, 109, 128, 142, 18
7]
Duplicate outliers :  [154, 65, 75, 66, 128]
```

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:

- Data points with index 154, 65, 75, 66 and 128 are considered outliers for more than one feature.
- Some outliers inside 3 times the interquartile range still have some information about the data. We can remove extreme outliers (outside of 3 times the interquartile range) to keep most information.

Feature Transformation

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

Implementation: PCA

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

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

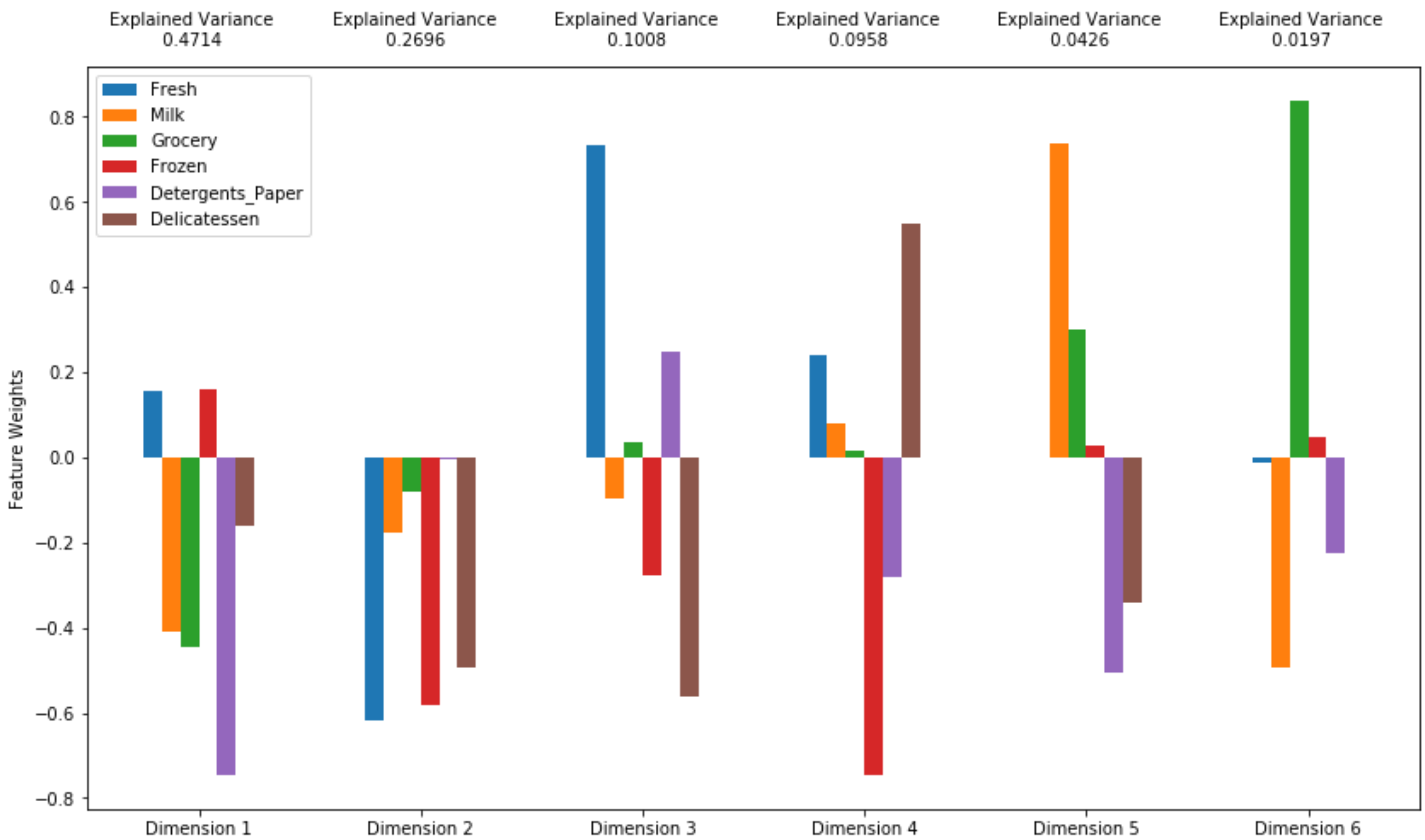
- Import `sklearn.decomposition.PCA` and assign the results of fitting PCA in six dimensions with `good_data` to `pca`.
- Apply a PCA transformation of `log_samples` using `pca.transform`, and assign the results to `pca_samples`.

In [9]:

```
from sklearn.decomposition import PCA
# TODO: Apply PCA by fitting the good data with the same number of dimensions as features
feature_dim = data.shape[1]
pca = PCA(n_components = feature_dim).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)
```



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 first and second principal component explained 72.52% (0.4993 + 0.2259) variance in the data.
- The first four components explained 92.79% variance in the data.
- The 1st dimension explains most variance on Detergents_Paper, Grocery and Milk. The feature weights are negative means larger negative dimension value implies larger spending on those categories. It could be used to represent customers from business hotel that needs detergents papers, groceries and milk for simple meals.
- The 2nd dimension explains most variance on Fessh, Frozen and Delicatessen. The feature weights are negative means larger negative dimension value implies larger spending on those categories. It could be used to represent customers from supermarkets that sells stuffs like meats or fishes and some food.
- The 3rd dimension explains most variance on Fresh and Delicatessen. Also, it explains some variance on frozen and detergents paper. Negative feature weights mean larger negative dimension value implies larger spending on those categories. Positive feature weights mean larger positive dimension value implies larger spending on them. We can see the signs of feature weights are different for Fresh and Delicatessen that means if one spends more on Fresh, he would spends less on Delicatessen, and vice versa. It could be used to represent customers from restaurants.
- The 4th dimension explains most variance on Frozen and Delicatessen. Also, it explains some variance on fresh and detergents paper. Negative feature weights mean larger negative dimension value implies larger spending on those categories. Positive feature weights mean larger positive dimension value implies larger spending on them. We can see the signs of feature weights are different for Frozen and Delicatessen that means if one spends more on Frozen, he would spends less on Delicatessen, and vice versa. It could be used to represent customers from food stores.

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 [10]:

```
# Display sample log-data after having a PCA transformation applied
display(pd.DataFrame(np.round(pca_samples, 4), columns = pca_results.index.val
ues))
```

	Dimension 1	Dimension 2	Dimension 3	Dimension 4	Dimension 5	Dimension 6
0	-1.9218	-1.5737	-1.1716	0.5587	-0.5763	-0.3368
1	-4.4135	-2.5808	1.2073	-0.4154	0.5645	0.1915
2	1.2233	-0.3553	1.8300	-1.0115	1.0407	0.8765

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 [11]:

```
# 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'])
```

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 [12]:

```
# 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	-1.9218	-1.5737
1	-4.4135	-2.5808
2	1.2233	-0.3553

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.

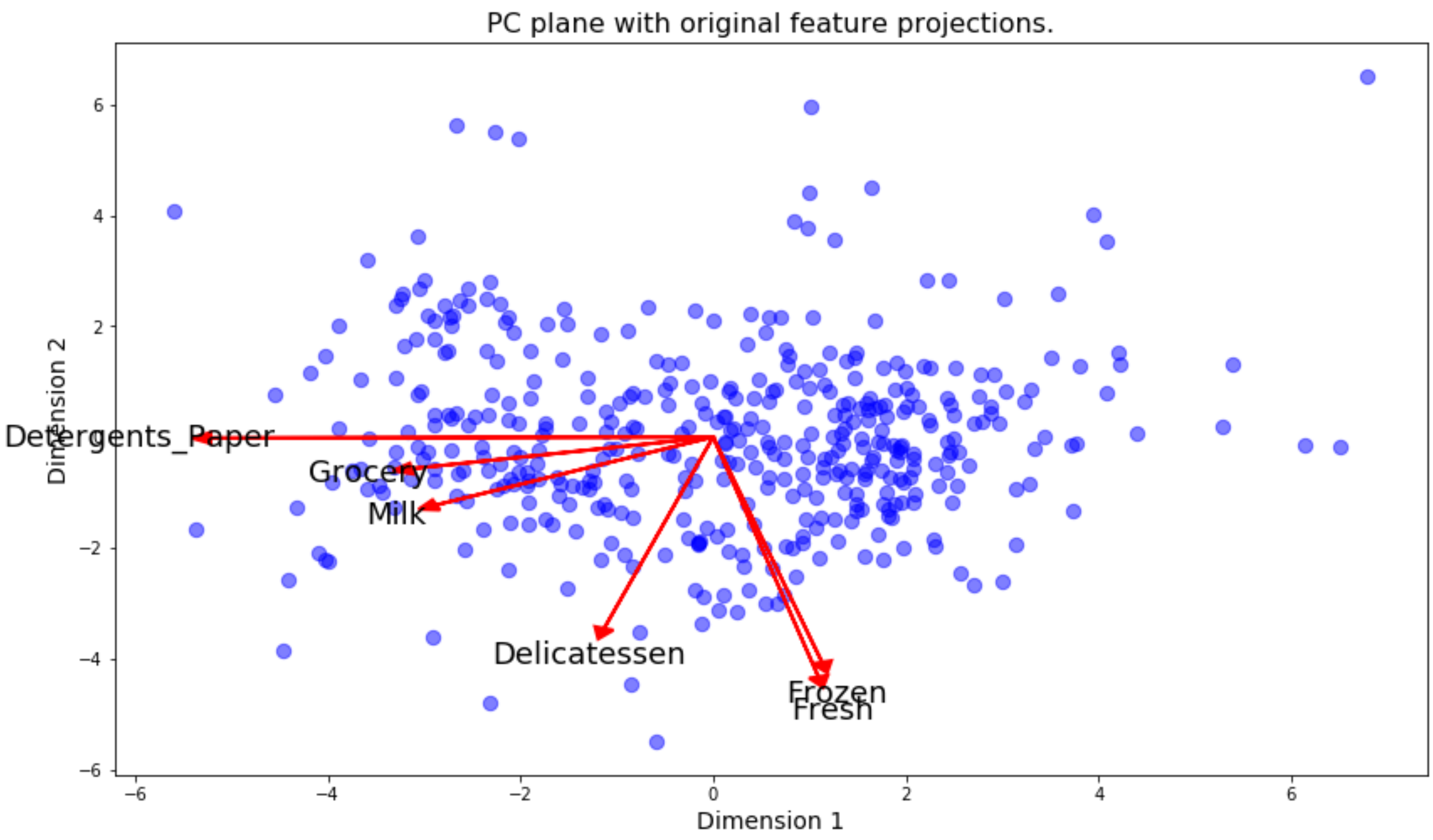
Run the code cell below to produce a biplot of the reduced-dimension data.

In [13]:

```
# Create a biplot
vs.biplot(good_data, reduced_data, pca)
```

Out[13]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x103f38be0>
```



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?

Clustering

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

Question 6

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

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

Answer:

- K-means algorithm is very fast and scalable for large dataset. The average complexity is O(knT), were n is the number of samples, T is the number of iteration and k is cluster number specified. It assumes clusters to be symmetrical sperical shape. It is a hard clustering algorithm and best suits for clearly separatable data.
- Gaussian Mixture Model (GMM) algorithm is a soft clustering algorithm. It's flexible on cluster shape and each data point has different level of membership (probability) for multiple clusters.
- From the biplot, we can see many features lie in similar direction and can be clearly separated. It would be better to choose soft clustering algorithm (e.g. GMM) instead of hard clustering algorithm (e.g. k-means). Besides, our dataset only has 440 samples. It's a relatively small size dataset and can be trained in a reasonable time for GMM.

Implementation: Creating Clusters

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

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

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

In [14]:

```
from sklearn.mixture import GaussianMixture
from sklearn.metrics import silhouette_score

for cluster_num in range(2,6) :
    # TODO: Apply your clustering algorithm of choice to the reduced data
    clusterer = GaussianMixture(n_components=cluster_num).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 cluste
rs chosen
    score = silhouette_score(reduced_data, preds)
    print("{} cluster sihouette score :".format(cluster_num), score)

clusterer = GaussianMixture(n_components=2).fit(reduced_data)
preds = clusterer.predict(reduced_data)
centers = clusterer.means_
sample_preds = clusterer.predict(pca_samples)
score = silhouette_score(reduced_data, preds)
print("2 cluster has best sihouette score :", score)
```

```
2 cluster sihouette score : 0.424940565438
3 cluster sihouette score : 0.337530716263
4 cluster sihouette score : 0.304525190458
5 cluster sihouette score : 0.356913522025
2 cluster has best sihouette score : 0.424940565438
```

Question 7

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

Answer:

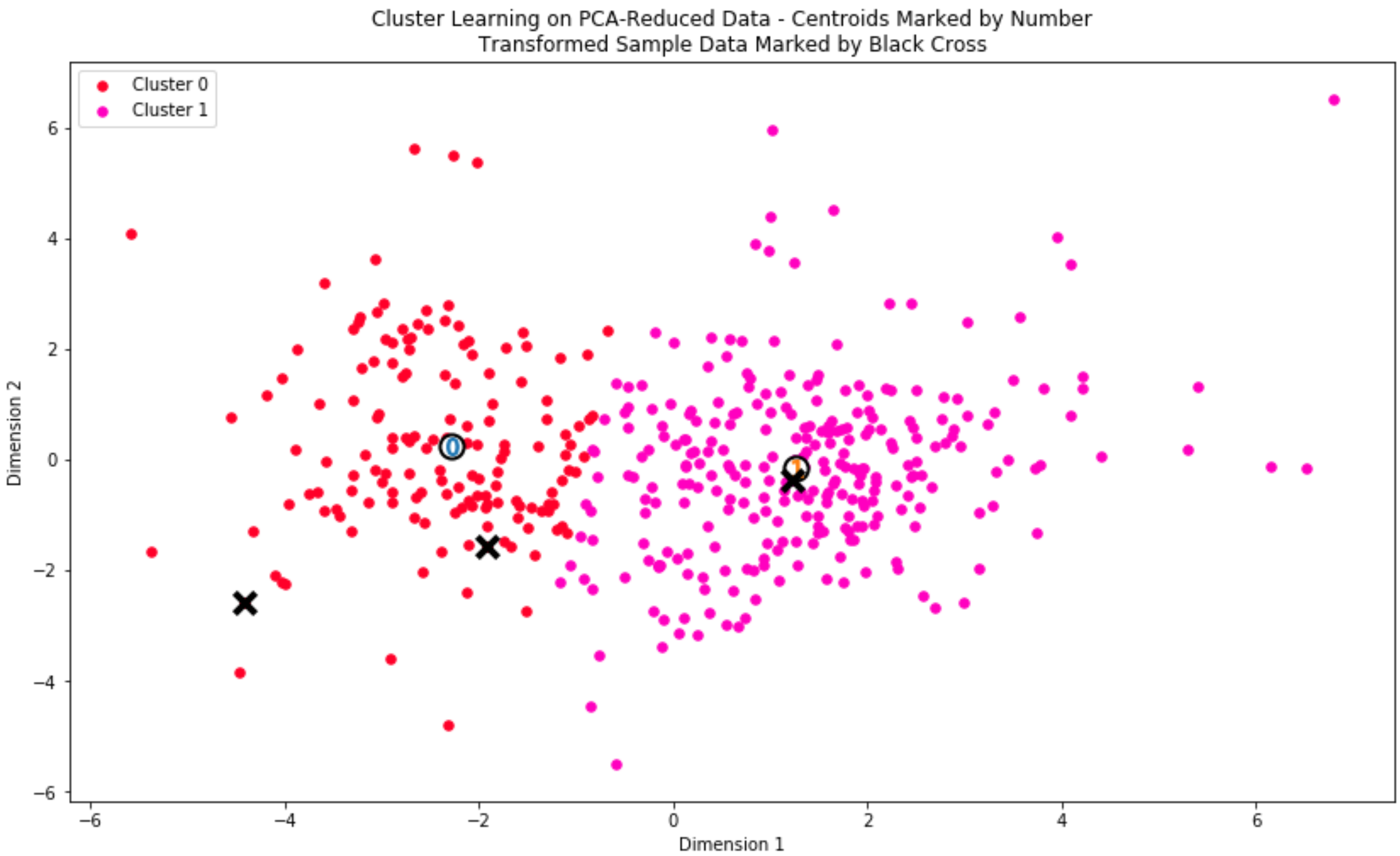
- I've tried 2, 3, 4 and 5 cluster and the sihouette scores are
  - 2 cluster : 0.424940565438
  - 3 cluster : 0.393771864134
  - 4 cluster : 0.372657784015
  - 5 cluster : 0.356594042952
- 2 cluster has the best sihouette score.

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 [15]:

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



Implementation: Data Recovery

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

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

- Apply the inverse transform to `centers` using `pca.inverse_transform` and assign the new centers to `log_centers`.
- Apply the inverse function of `np.log` to `log_centers` using `np.exp` and assign the true centers to `true_centers`.

In [16]:

```
# 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	3976.0	8200.0	12656.0	886.0	4964.0	1057.0
Segment 1	8832.0	2052.0	2679.0	1977.0	355.0	725.0

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:

- Segment 0 has much higher value than average in Milk, Grocery and Detergents_paper (near 75 percentile). It also has lower value than average in Fresh and Frozen (25~50 percentile). It represents customers belonging to cluster 0 spending more on Milk, Grocery and Detergents_paper, but less on Fresh and Frozen. These customers may come from hotels.
- Segment 1 has much lower value than average in Milk, Grocery and Detergents_paper (near 25 percentile). It also has higher value than average in Fresh and Frozen (50~75 percentile). It represents customers belonging to cluster 1 spending less on Milk, Grocery and Detergents_paper, but more on Fresh and Frozen. These customers may come from supermarkets.

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 [17]:

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

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

Answer:

- Sample points 0 and 1 are predicted to be in Cluster 1 and sample point 2 is predicted to be in Cluster 0.
- Sample point 0 is slightly above 75 percentile for Milk, 50~75 percentile for Grocery and slightly below 75 percentile for Detergents_Paper. It has higher values in Milk, Grocery and Detergents_Paper. It should be in Cluster 1 and indeed be predicted to be in Cluster 1.
- Sample point 1 has much higher values than 75 percentile for Milk, Grocery and Detergents_Paper. As a result, it should be in Cluster 1 and indeed be predicted to be in Cluster 1.
- Sample point 2 has lower values for Milk and Detergents_Paper (25~50 percentile), slightly high values for Grocery and Frozen (50~75 percentile), and much higher value for Fresh (>75 percentile). It comes close to Cluster 0 and indeed be predicted to be in Cluster 0.

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.

Question 10

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

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

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

Answer:

- We can first pick two small subsets of customers who have similar distribution near the center of each cluster as representatives of each cluster. For one cluster, we change the delivery service and remains the same for the other. Then we survey both parties to see if it reacts positively. If it reacts positively, we can try another two subsets of customers who have features slightly farer than cluster center as second round and so on till we have negative feedbacks. Also, we can examine different combination and weights of features to see if we can find some hidden behaviors through these processes.

Question 11

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

- How can the wholesale distributor label the new customers using only their estimated product spending and the **customer segment** data?

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

Answer:

- We can use estimates for anticipated annual spending of each product category as features and customer segment as labels to train a supervised learning model that we choose. After some training, validation and testing, we may have a good supervised model. Then we can apply the model to predicted customer segment for new customers and determine their delivery service based on the predicted customer segment.

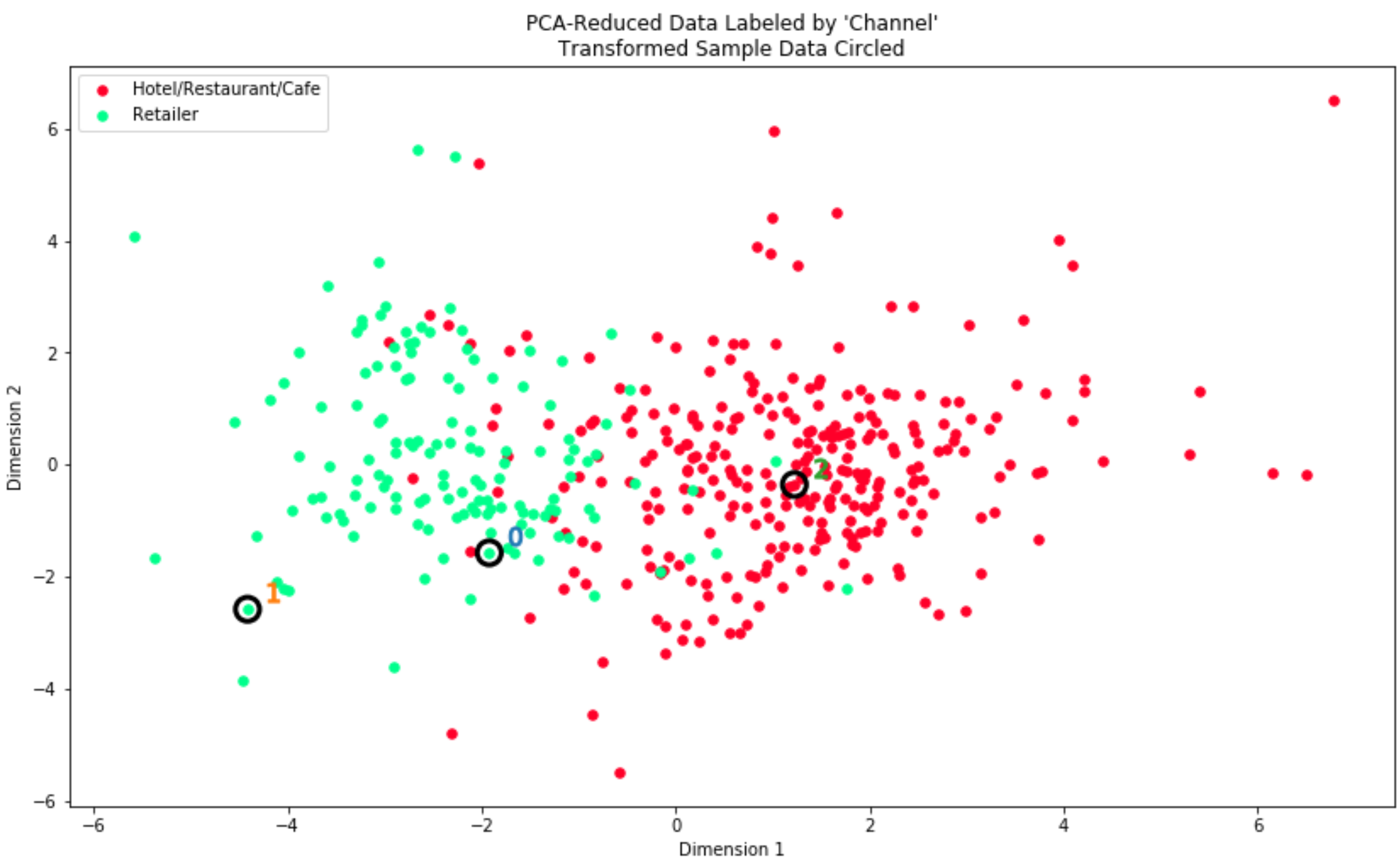
Visualizing Underlying Distributions

At the beginning of this project, it was discussed that the `'Channel'` and `'Region'` features would be excluded from the dataset so that the customer product categories were emphasized in the analysis. By reintroducing the `'Channel'` feature to the dataset, an interesting structure emerges when considering the same PCA dimensionality reduction applied earlier 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 [18]:

```
# Display the clustering results based on 'Channel' data
vs.channel_results(reduced_data, outliers_removed, pca_samples)
```



Question 12

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

Answer:

- It fits the number of clusters I have chosen and both clusters distribute similar to my clustering result. Sample points 0 and 1 remain in the same cluster (Retailer) and sample point 2 is in the other cluster (Hotel/Restaurant/Cafe). My previous definition for clusters are hotels (generally higher value in dimension 1) and supermarkets (generally lower value in dimension 1). It's consistent with the new introduced classification.

> **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.