customer_segments

September 1, 2018

1 Machine Learning Engineer Nanodegree

1.1 Unsupervised Learning

1.2 Project: Creating Customer Segments

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

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

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

1.3 Getting Started

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

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

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

In [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 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 = [66,431,100]

        # 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	9	1534	7417	175	3468	27
1	8533	5506	5160	13486	1377	1498
2	11594	7779	12144	3252	8035	3029

1.4.2 Question 1

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

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

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

- Fresh: 12,000
- Milk: 5,796
- Grocery: 7,951

- Frozen: 3,071
- Detergents_paper: 2,881
- Delicatessen: 1,524

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

Answer: Intuition tells me that there are at least 3 customer segments. These are most likely

- Gas Station or Local Convenience Shop
  - Sample# 0 is a good example of this customer
  - This customer will most likely be characterized by an average or more of Groceies and Detergents Paper spending than overall. Other data items would be pretty small as compared to overall average. All the averages below confirm this.
    * Customer buys Fresh at 3 and overall average is 12,000
    * Customer buys Milk at 1,534 and overall average is 5,796
    * Customer buys Grocery at 7,417 and overall average is 7,951
    * Customer buys Frozen at 175 and overall average is 3,071
    * Customer buys Detergents_paper at 3,468 and overall average is 2,881
    * Customer buys Delicatessen at 27 and overall average is 1,524
- Other Wholesale Retailers
  - Sample# 1 is a good example of this customer
  - This customer will most likely be characterized by an above average spending across all data items. We can think of this customer as Business to Business transaction. They buy from our wholesale and in turn retail to other small retail shops. The following averages confirm this.
    * Customer buys Fresh at 112,151 and overall average is 12,000
    * Customer buys Milk at 29,627 and overall average is 5,796
    * Customer buys Grocery at 18,148 and overall average is 7,951
    * Customer buys Frozen at 16,745 and overall average is 3,071
    * Customer buys Detergents_paper at 4,948 and overall average is 2,881
    * Customer buys Delicatessen at 8,550 and overall average is 1,524
- Markets or Local Food Supermarket
  - Sample# 2 is a good example of this customer.
  - This customer will buy average of all data items. if possible, most likely they have more than average Fresh spending. This is because Food Supermarket tend to have fresh produce sections that generally tend to be sold or thrown away quickly. In either case, i would expect more than average spending with on Fresh. Some Food Supermarkets have delicatessen sections while others don't. I think this spending will be lower than overall average. The following are the average of a possible matching sample
    * Customer buys Fresh at 11,594 and overall average is 12,000
    * Customer buys Milk at 7,779 and overall average is 5,796
    * Customer buys Grocery at 12,144 and overall average is 7,951
    * Customer buys Frozen at 3,252 and overall average is 3,071
    * Customer buys Detergents_paper at 8,035 and overall average is 2,881
    * Customer buys Delicatessen at 3,029 and overall average is 1,524

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]: # Importing the respective Libraries
        from sklearn.model_selection import train_test_split
        from sklearn.tree import DecisionTreeRegressor

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

        # TODO: Split the data into training and testing sets(0.25) using the given feature as t
        # Set a random state.
        X_train, X_test, y_train, y_test = train_test_split(new_data, data['Delicatessen'], test

        # TODO: Create a decision tree regressor and fit it to the training set
        regressor = DecisionTreeRegressor(random_state = 66)
        regressor.fit(X_train, y_train)

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

1.4.4 Question 2

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

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

Answer: I choose Fresh feature to be predicted from other features. The predicted score was -1.11, which is pretty good in our case. The negative R^2 score implies that model cannot fit the data and thus Fresh is an important feature to consider. I was also curious to see other features so i checked the score on them as well.

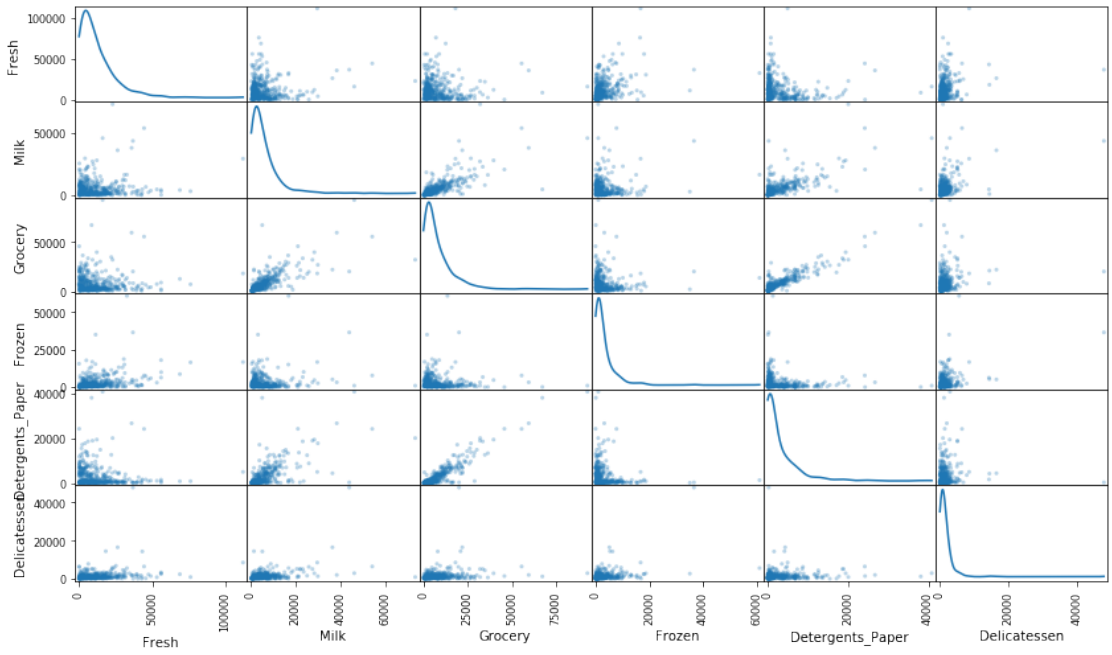
Feature	Score
Fresh	-1.11
Milk	-0.12
Grocery	+0.59
Frozen	-0.58
Detergents_Paper	+0.74
Delicatessen	-1.67

it looks like Fresh, Milk, Frozen and Delicatessen are important features to consider. Grocery and Detergents_Paper might be removed in feature selection step.

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');
```



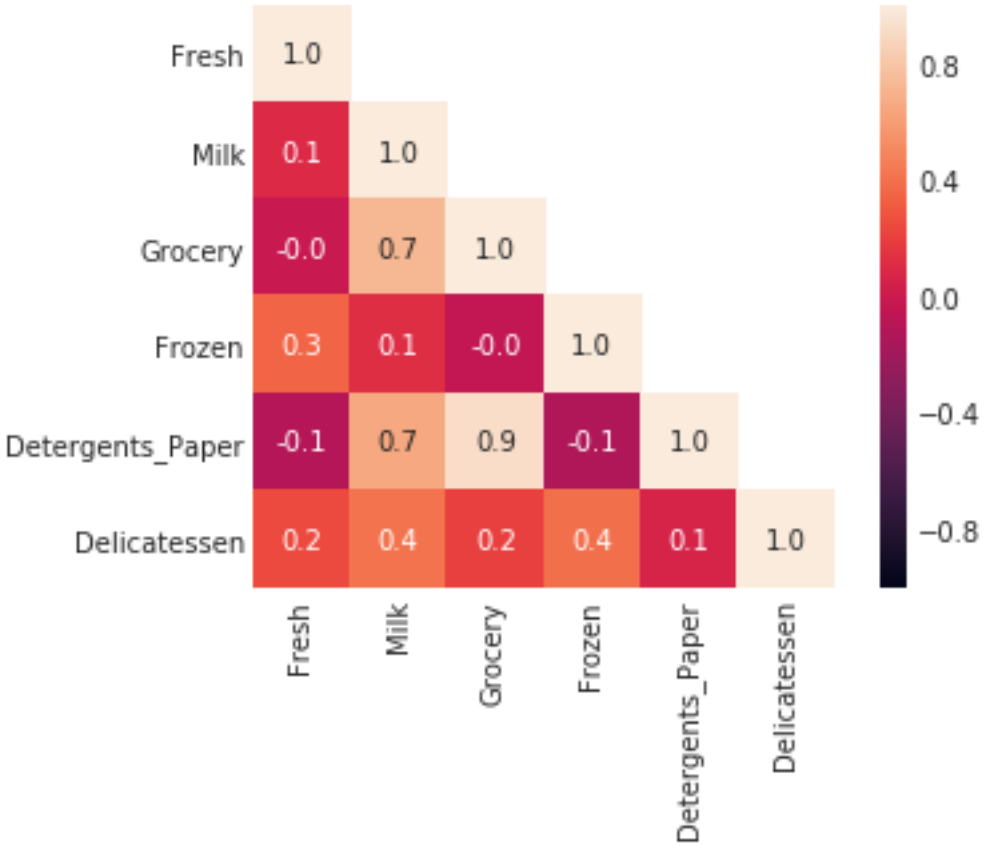
1.4.6 Question 3

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

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

In [6]:
```
import seaborn as sns

corr = data.corr(method='pearson')
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask,1)] = True
with sns.axes_style("white"):
    ax = sns.heatmap(corr, mask=mask, vmax=1,vmin=-1, square=True,annot=True, fmt='.1f')
```



Answer: Based on the correlation matrix, the following seems to be true

1. Grocery and Detergents_Paper are highly correlated with correlation coefficient of 0.9.
2. Milk and Detergents_Paper are also highly correlation with a correlation coefficient of 0.7.
3. Milk and Grocery are also highly correlation with a correlation coefficient of 0.7.

This means that we can either drop two features from Grocery, Milk and Detergents_paper or use a dimension reduction technique to represent these three features with a new data item that has no correlation with Fresh, Frozen and Delicatessen.

For the distribution graphs, all six features are skewed towards the right. it seems like there are outliers in this dataset as well.

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

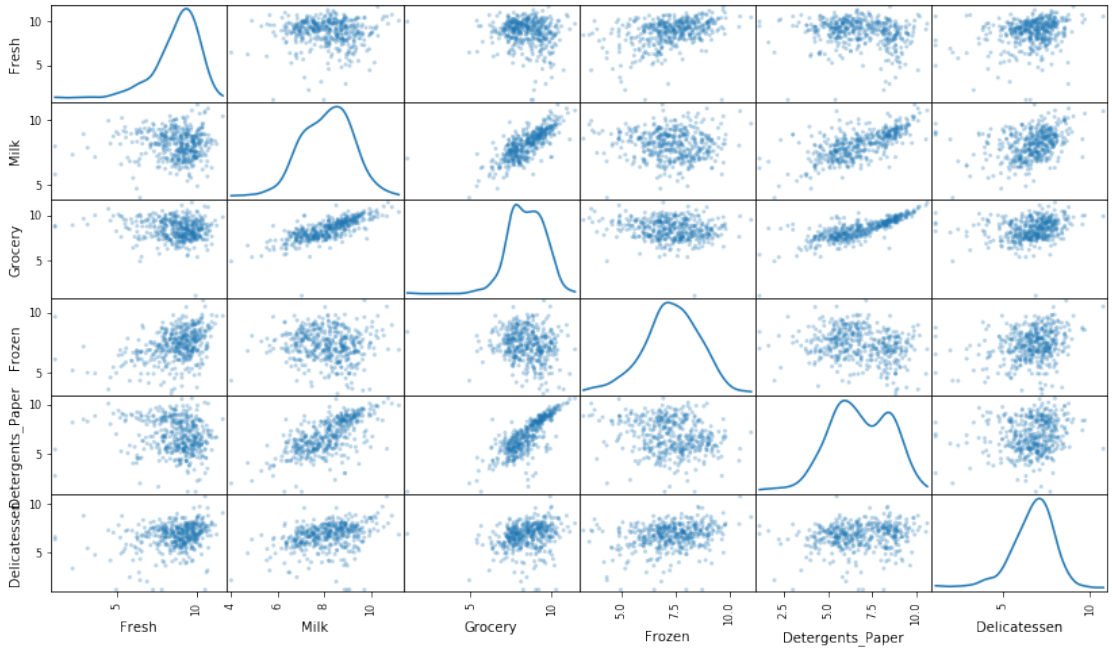
If data is not normally distributed, especially if the mean and median vary significantly (indicating a large skew), it is most often appropriate to apply a non-linear scaling — particularly for financial data. One way to achieve this scaling is by using a Box-Cox test, which calculates the best power 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.copy())

        # 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

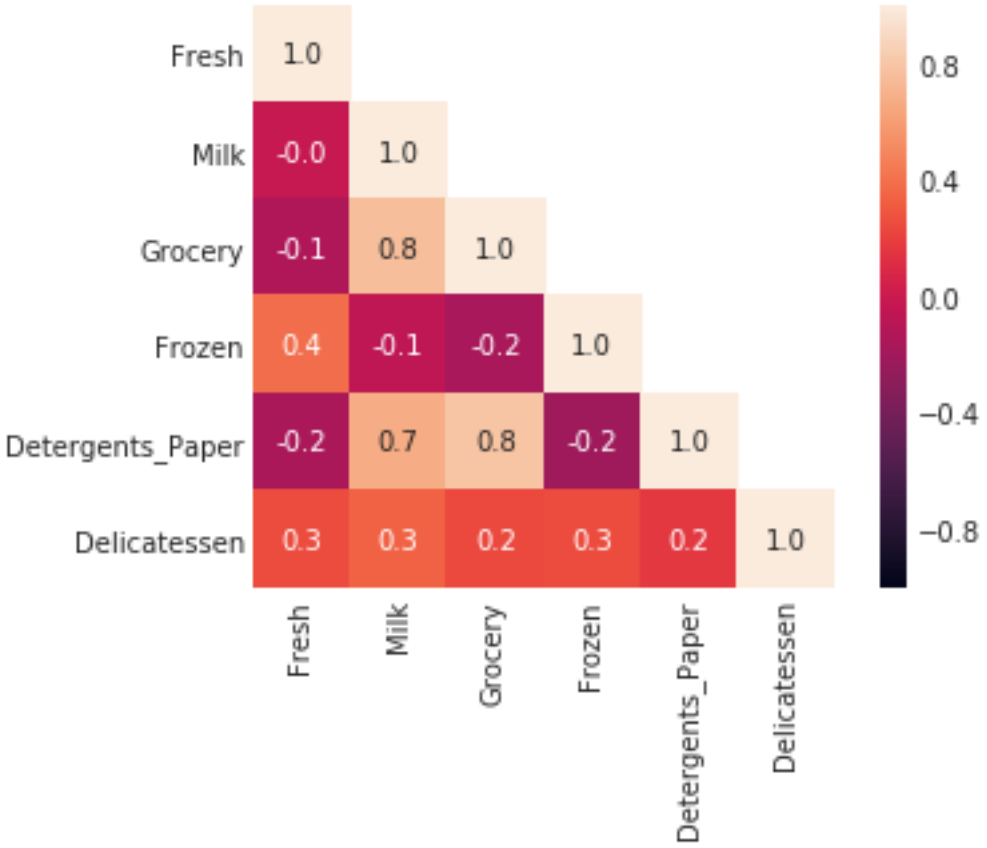
After applying a natural logarithm scaling to the data, the distribution of each feature should appear much more normal. For any pairs of features you may have identified earlier as being correlated, observe here whether that correlation is still present (and whether it is now stronger or weaker than 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	2.197225	7.335634	8.911530	5.164786	8.151333	3.295837
1	9.051696	8.613594	8.548692	9.509407	7.227662	7.311886
2	9.358243	8.959183	9.404590	8.087025	8.991562	8.015988

```
In [9]: # Checking How Correlation has Changed
        corr = log_data.corr(method='pearson')
        mask = np.zeros_like(corr)
        mask[np.triu_indices_from(mask,1)] = True
        with sns.axes_style("white"):
            ax = sns.heatmap(corr, mask=mask, vmax=1,vmin=-1, square=True,annot=True, fmt='.1f')
```



it looks correlation has grown slightly weaker.

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

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

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

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

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

        # 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
```

1.5.4 Question 4

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

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

Answer: Just looking at the distribution plots, we can see many outliers per each feature. Now that we have identified outliers per tukey's method, i think we can safely remove data points that are considered outliers for at least 2 features. some examples are as following

1. #75 is an outlier in Grocery and Detergents_Paper.
2. #154 is an outlier in Delicatessen, Grocery and Milk.
3. #66 is an outlier in Delicatessen and Fresh.

Having outliers in a multi-dimensonal data increase the sparsity of the dataset. Essentially, it increases the dimensional space between each data point so a learning algorithim that is space dependent like K-Means will not perform well.

A common analogy can be space and galaxies. There are different galaxies in the universe. Each galaxy can be thought of as a concentrated collection of data points. Applying K-Means on a data like this will hopefully give us the clusters; which are the galaxies here.

In this manner, if the universe expands than the collection of data points will drift away from each other and each data point will no longer form a concentrated collection. In other words, there will sparsity in the dataset. it will be very hard for K-Means to perform well here.

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.

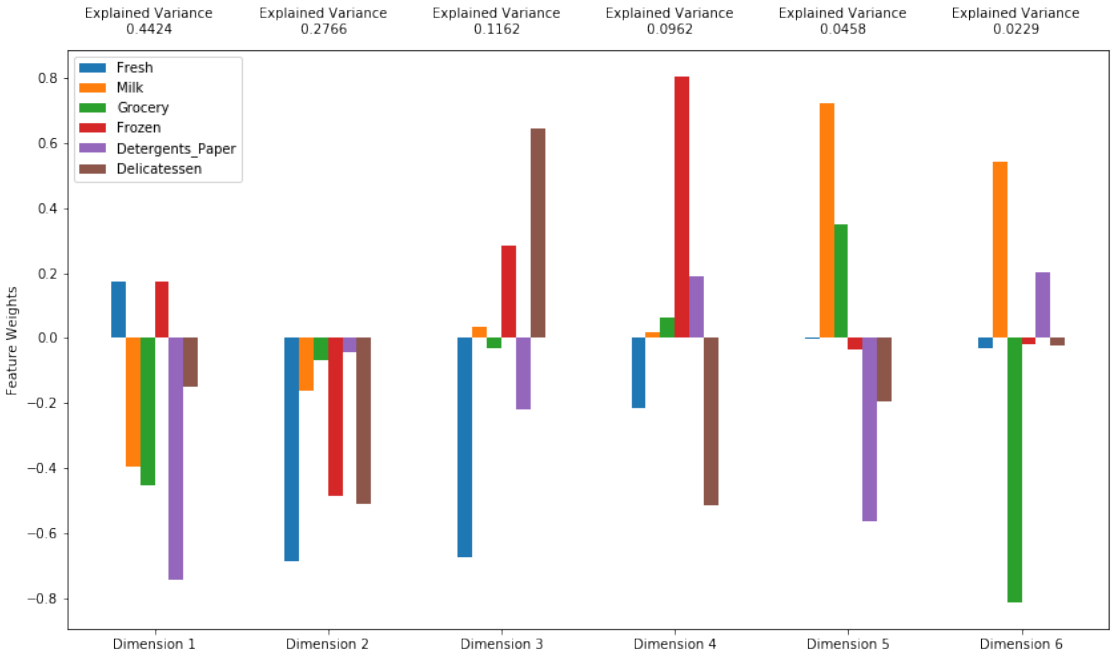
In the code block below, you will need to implement the following: - Import `sklearn.decomposition.PCA` and assign the results of fitting PCA in six dimensions with `good_data` to `pca`. - Apply a PCA transformation of `log_samples` using `pca.transform`, and assign the results to `pca_samples`.

In [11]:
```
from sklearn.decomposition import PCA

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

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

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



1.6.2 Question 5

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

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

Answer: The cumulative and individual variance explained by each component and what each dimension represents can be summed up in the following table

Principal Component	Individual Variance	Cumulative Variance	Possible Customer Segment
First	44.24%	44.24%	Local Food Supermarket
Second	27.66%	71.9%	Restaurant
Third	11.62%	83.52%	Convenience Store
Fourth	9.62%	93.14%	Gas Station
Fifth	4.58%	97.72%	Cafe
Sixth	2.29%	100.00%	Speciality Food Store

My reasoning for each possible customer segment can be explained as following

1. The first dimension paired Milk, Grocery and Detergents_Paper in a positive direction. This customer is most likely a local food supermarket. These three things are what the local food supermarket sells to individual households. The individual variance explained by this group is 44.24% meaning that this is the largest customer segment.

2. The second dimension paired Fresh, Frozen and Delicatessen in a negative direction. This customer is most likely some sort of restaurant. A restaurant will buy Fresh, Frozen and Delicatessen items for preparing and selling food items to patrons. The variance explained by this dimension is 27.66% so this is relatively large customer segment.

3. The third dimension paired Delicatessen and Frozen positively and a strong negative direction in Fresh. In Other words, this customer buys Delicatessen and Frozen togather but does not buy Fresh. This customer is most likely a small convenience store or corner store. A small corner store will not have a Fresh section but a lot of Delicatessen and Frozen items. The variance explained by this dimension is 11.62% so this is relatively large customer segment.

4. The fourth dimension paired Frozen and Detergents_Paper positively and a negative direction in Delicatessen. So this customer buys Frozen and Detergents_paper but not Delicatessen. This customer is most likely a gas station store. A Gas station will carry Frozen and Detergents_Paper items but not Delicatessen items. The variance explained by this dimension is 9.62% so this is relatively small customer segment.

5. The fifth dimension paired Fresh and Milk positively and a negative direction in Detergents_Paper. So this customer buys Fresh and Milk but not Detergents_paper. So this customer is most likely a Cafe. A Cafe will need Milk to make English tea and Fresh items to cafe oriented food items. From what i know, this data came from Portugal and Portugal do have a cultural affinity with milk tea so it makes sense that their cafe's would serve milk tea. The variance explained by this dimension is 4.58% so this is relatively small customer segment.

6. The sixth dimension paired Grocery weakly with Fresh, Frozen and Delicatessen in one direction and Milk and Detergents_Paper in another direction. So this customer buys Grocery but not Milk and Detergents_Paper. So This customer is most likely a Speciality Food Store. From what i know, a speciality store like an indian grocery store does not carry perishable items like Milk. The respective indian grocery store will also not carry detergents_paper because the margins are much lower. The indian grocery store will buy a lot of grocery items and small portions of Fresh, Frozen and Delicatessen items as consistent with this dimension. The variance explained by this dimension is 2.29% so this is smallest customer segment.

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

	Dimension 1	Dimension 2	Dimension 3	Dimension 4	Dimension 5	\
0	-1.9212	7.2733	1.2808	1.6833	-0.4322	
1	-0.2331	-1.7325	0.7459	1.4789	-0.0624	
2	-2.3702	-1.7971	0.1871	0.3020	-0.5955	

	Dimension 6
0	-0.2275
1	0.2067
2	0.0546

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

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

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

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

1.6.5 Observation

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

```
In [14]: # 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      -1.9212       7.2733
1      -0.2331      -1.7325
2      -2.3702      -1.7971
```

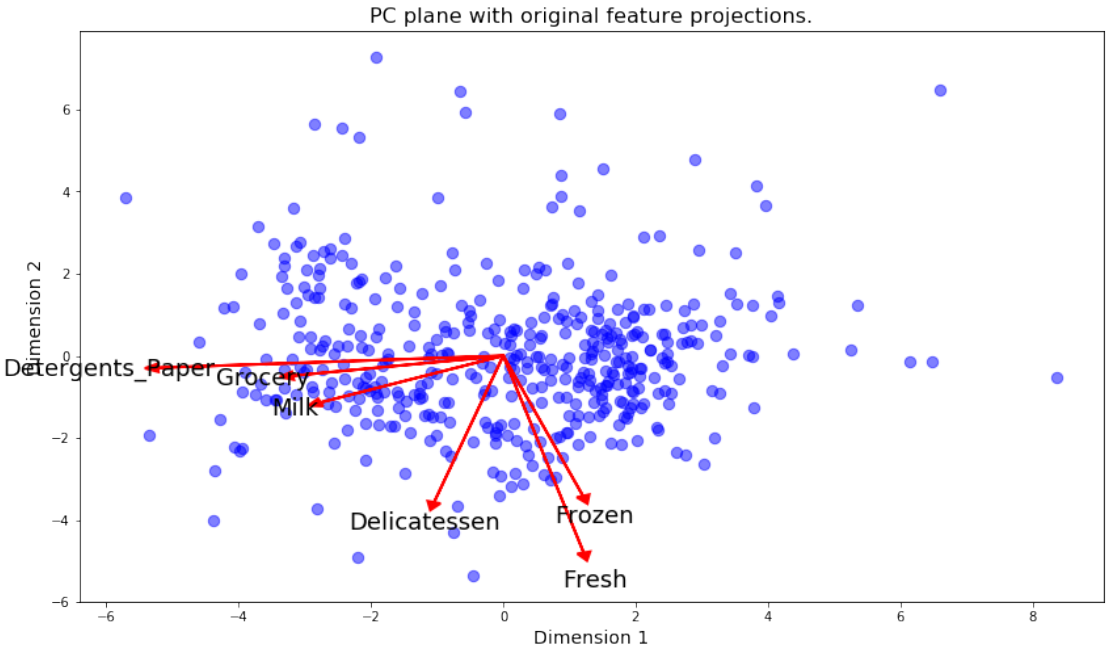
1.7 Visualizing a Biplot

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

```
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7c5acf7860>
```



1.7.1 Observation

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

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

1.8 Clustering

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

1.8.1 Question 6

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

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

Answer: I would say the following about Clustering

- The main advantage of K-Means clustering algorithm is that it is easily scalable to big data. K-Means starts with a random centers and starts converging the data points towards the centroid per each iteration. This means that K-Means is a hard clustering algorithm. K-Mean assumes that each data point either belongs to one cluster or another. In short, This is a parametric hard clustering learning algorithm.

- The main advantage of Gaussian Mixture clustering algorithm is that it has fewer assumptions. it can be thought of as non-parametric or general version of K-Means. it uses EM Algorithm to find a solution and assigns a probability to each data point for the cluster it might belong to. In short, This is a non-parametric soft clustering learning algorithm.

- For soft and hard clustering, i think soft clustering would be the way to go. I can imagine a customer as a local food supermarket having a small cafe inside it. From the possible segments i have defined above, this customer would fall into both clusters of Local Food Supermarket and Cafe. In other words, there is some overlap between customer segment clusters. In short, the general structure of data is inclined to soft clustering.

- I would say that Gaussian mixture would be slighly preferred algorithim here because

    1. The general structure of Data is soft clustering. There is some overlap of customer segments. Therefore, we need an algortithm like Gaussian Mixture that is preferred for Soft Clustering.
    2. Data is relatively normally distributed due to transformations and removal of outlier data points but i would still prefer to use Gaussian Mixture here. Fewer assumptions are always a good choice.

Since, There are two principal components that have a weight of 71.9%. i.e. we know k=2. I think both Gaussian Mixture and K-Means would work fine here.

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 [16]:
```
from sklearn.metrics import silhouette_score
from sklearn.cluster import KMeans
from sklearn.mixture import GaussianMixture

# TODO: Apply your clustering algorithm of choice to the reduced data
#clusterer = KMeans(n_clusters=2, random_state=66)
clusterer = GaussianMixture(n_components =3, random_state=66)
clusterer.fit(reduced_data)

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

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


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

# TODO: Calculate the mean silhouette coefficient for the number of clusters chosen
score = silhouette_score(reduced_data,preds,random_state=66)
print(score)
```

```
0.417598126779
```

1.8.3 Question 7

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

Answer: I tried both K-Means and Gaussian Mixture clustering. Below are the silhouette scores for different clusters numbers that i tried

# of Clusters	K-Means Silhouette Score	GM Silhouette Score
k=2	41.91%	41.03%
k=3	39.30%	41.75%
k=4	33.03%	30.78%
k=5	35.00%	32.67%
k=6	35.95%	27.47%
k=7	36.51%	32.44%

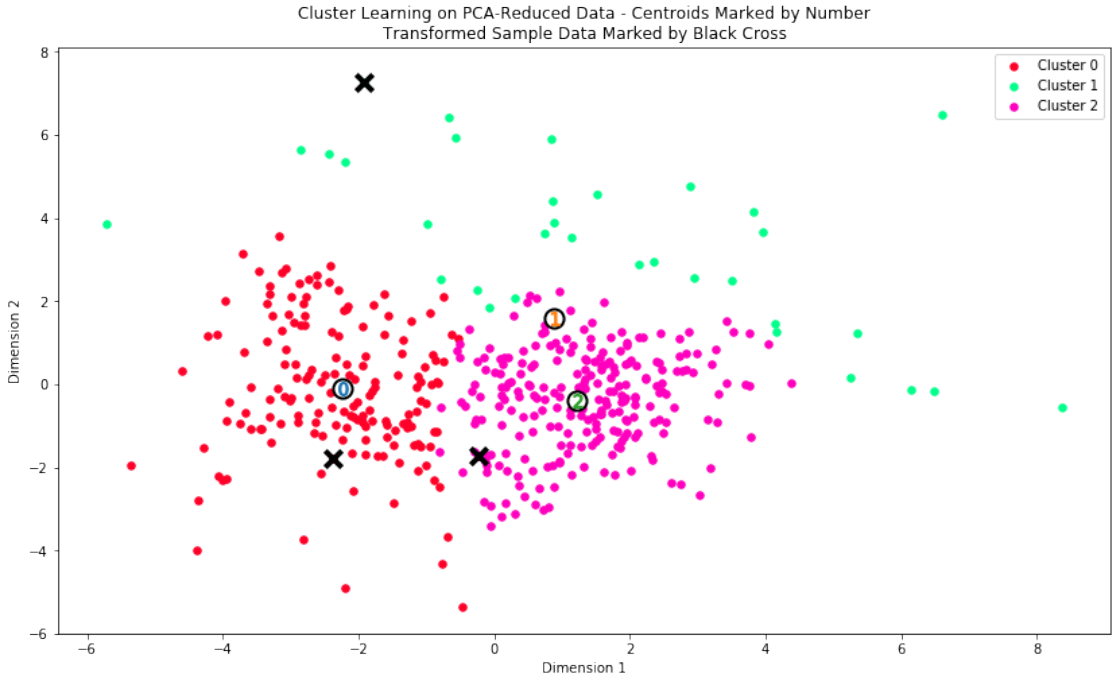
For K-Means,the best score of 41.91% happens when k=2. Which is consistent with out observations from principal component analysis.

For Gassusian Mixture,the best score of 41.75% happens when k=3. Which is a bit inconsistent with our principal component analysis. However, There is good chance that is a good chance two customer segments overlap.

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 [17]: # 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 [18]: # 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	4481.0	8226.0	12835.0	1057.0	4679.0	1148.0
Segment 1	2402.0	1836.0	2786.0	788.0	431.0	304.0
Segment 2	9987.0	2212.0	2731.0	2211.0	362.0	797.0

1.8.6 Question 8

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

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

Answer: Looking at both Segments, we can say the following

1. Segment 0 is most likely a local food supermarket. Looking at mean numbers for each feature; This segement buys a little below mean of Fresh, Milk, Grocery and Frozen. They

also tend to buy Detergents_Paper and Delatessen much lower than mean values. This is consistent with what a supermarket will buy.

2. Segment 1 is most likely a resturant. However, looking at mean numbers, it seems like this cluster is overlapping with cafe and convenience store segments. The respective observations show that this customers buys more than average for Milk,Grocery and Detergents_Paper and buys less than average Fresh. Furtheremore, the customer segments buys very little with Frozen while Fresh and Delicatessen are close to average. i think this cluster is not consistent with what a restaurant will buy. The simple explanation is that this segment is overlapping with other segments of convenience store and a cafe.

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

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

Answer: Let see what those samples look like

```
In [20]: display(samples)
```

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	9	1534	7417	175	3468	27
1	8533	5506	5160	13486	1377	1498
2	11594	7779	12144	3252	8035	3029

For each sample point, i would say the following

- Sample 0 is predicted as a restaurant. This data point is not consistent with what a restaurant will buy. I looked back at the data and realized that this point was actually an outlier. it makes sense that it doesn't fit perfectly into restaurant segment.
- Sample 1 is predicted as a local food supermarket. Looking at mean numbers, This data point is consistent with what a supermarket will buy.
- Sample 2 is predicted as a restaurant. Looking at mean numbers, This data point is consistent with what a restaurant will buy.

1.9 Conclusion

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

1.9.1 Question 10

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

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

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

Answer: Generally, a lot of companies will roll out some kind of Pilot program to see what the effect is of a new change or process. In the same manner, the wholesale distributor can create pilot program for select customers that represent different customer segments and start an expedited delivery service of 3 days. They can compare this pilot group to normal customers that are getting the normal 5 day delivery service accross different customer segments. We need to use the customer segments here because different groups of customers will react differently to a fast service.

For Example, a customer segment like restaurant will be sensitive to fast delivery service because they order a lot of fresh items. However, a customer segment like gas station stores, who buy a lot of detergents_paper and frozen will not be sensitive to change. In Short, the effect of delivery service will vary depending on customer segment.

In Conclusion, the wholesale distribution can roll out a pilot program accross customer segments for 3 day delivery service and then compare the results with existing customers that are still receiving 5 Day delivery service. The pilot program should be a large enough to be of statistical significance. I would guess as 25% of customers.

1.9.2 Question 11

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

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

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

Answer: We can use the engineered feature of Local Food Supermarket and Restaurant to build a supervised learning model. Essentially, the problem will change to predict customer segment for these 10 new customers. Here the customer segment can be Local Food Supermarket or restaurant. We can train the model on this earlier dataset and use the customer segment clusters that the unsupervised learning has yielded. After that, the 10 new customer's segment can predicted from this model.

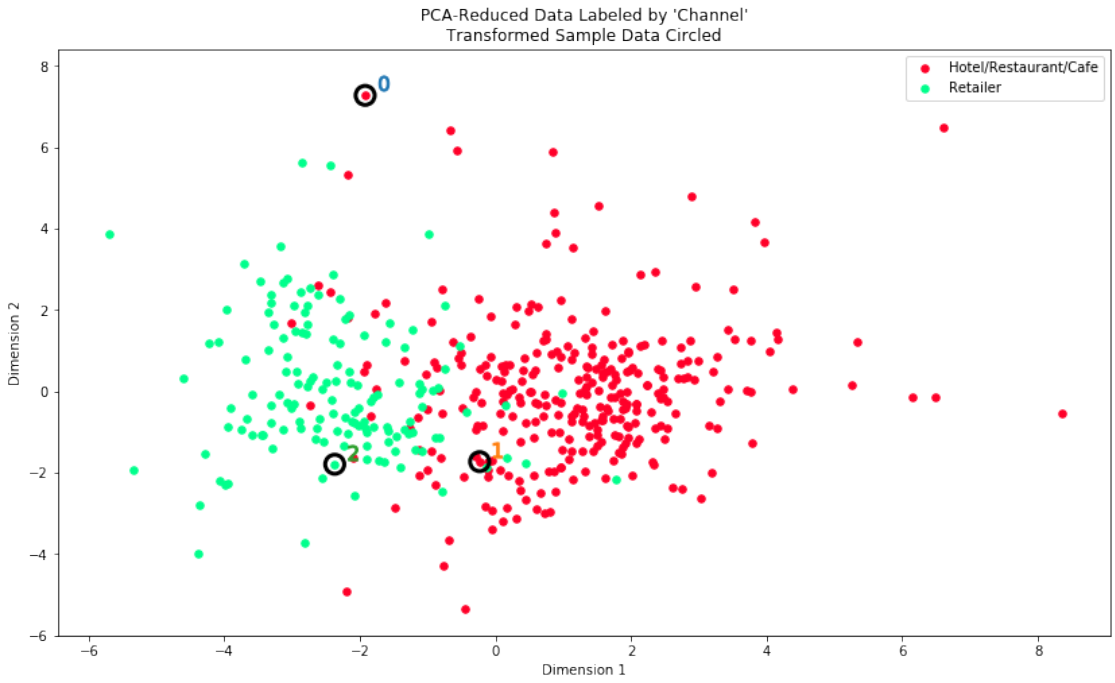
In short, we can train the supervised learner on original customers and the target variable can be the engineered customer segments that were yielded from above analysis.

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



1.9.4 Question 12

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

Answer: This is really interesting. Some of the main points i would say are

1. I didn't think of a customer segment labelled as Hotel. Thats why in my earlier analysis, i was trying to put a lot of customers into restaurant category. it makes sense that these customers were actually Hotel. Regardless, we confirmed that there are at least 2 customer segments in this data and the underlying data confirms this now.

2. As mentioned early, there is overlap of customer segments. In the above plot,we can see some retailers near Hotel/restaurant/Cafe cluster and vice versa. This is consistent with what i perceive the underlying data will be like. i.e. Some retailers will have a restaurant/cafe inside them so they are in both clusters.

3. Regardless of naming the customers segments, i think we did a good job of identifying two clusters. it looks like Hotel/Restaurant/Cafe is Segment 0 and Retailer is Segment 1 from earlier analysis. I did label them incorrectly but looking back at the data, it seems that these labels are more approriate. So i think that i am consistent with analysis but incorrect in naming these segments.

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.