customer_segments

October 31, 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.

```python
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")
            display(data.head())
            data.drop(['Region', 'Channel'], axis = 1, inplace = True)
            print("Wholesale customers dataset has {} samples with {} features each.".format(*da
            display(data.head())
            #length of the data
            print("The length of the dataset is",len(data))
        except:
            print("Dataset could not be loaded. Is the dataset missing?")
```

```
   Channel  Region  Fresh  Milk  Grocery  Frozen  Detergents_Paper  \
0        2       3  12669  9656     7561     214              2674
1        2       3   7057  9810     9568    1762              3293
2        2       3   6353  8808     7684    2405              3516
3        1       3  13265  1196     4221    6404               507
4        2       3  22615  5410     7198    3915              1777

   Delicatessen
0          1338
1          1776
2          7844
3          1788
4          5185
```

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

```
   Fresh  Milk  Grocery  Frozen  Detergents_Paper  Delicatessen
0  12669  9656     7561     214              2674          1338
1   7057  9810     9568    1762              3293          1776
2   6353  8808     7684    2405              3516          7844
3  13265  1196     4221    6404               507          1788
4  22615  5410     7198    3915              1777          5185
```

```
The length of the dataset is 440
```

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

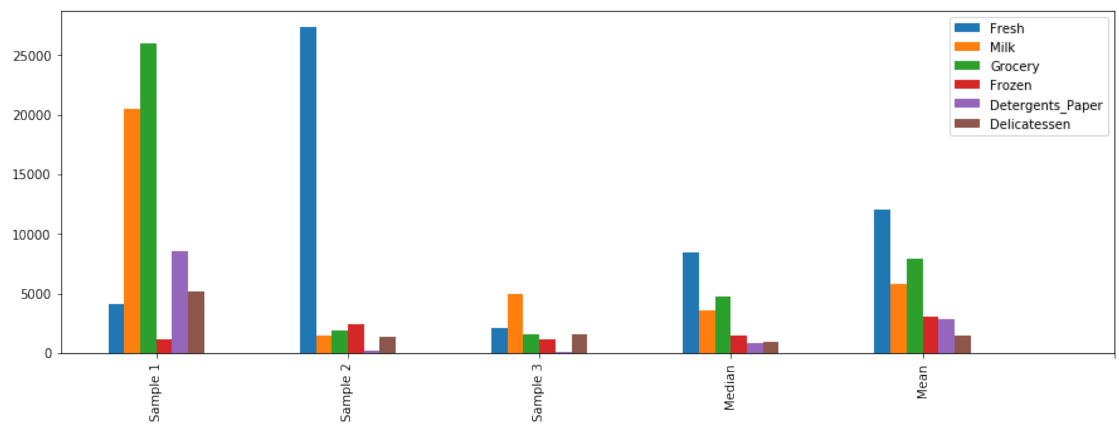
To get a better understanding of the customers and how their data will transform through the analysis, it would be best to select a few sample data points and explore them in more detail. In the code block below, add **three** indices of your choice to the `indices` list which will represent the customers 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 = [28,54,271]
```

```
# 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   4113  20484    25957    1158              8604          5206
1  27329   1449     1947    2436               204          1333
2   2083   5007     1563    1120               147          1550
```

```
In [4]: import matplotlib.pyplot as plt
        import seaborn as sns

        samples_for_plot = samples.copy()
        samples_for_plot.loc[3] = data.median()
        samples_for_plot.loc[4] = data.mean()

        labels = ['Sample 1', 'Sample 2', 'Sample 3', 'Median', 'Mean']
        samples_for_plot.plot(kind='bar', figsize=(15, 5))
        plt.xticks(range(6), labels)
        plt.show()
```



1.4.2 Question 1

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

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

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

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

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

Answer:

Since this is an intuition answer which I may not be able to tell the correct prediction but depending upon the highest score of the category where the user spends the most of his time and money to buy those items

Given the above three customers which the dataset gives the idea about the establishment which they have visited

```
a)Customer 1 which the customer id is 28 and we can see that the Grocery is having high score co
other scores which are having low scores on the Fresh,Milk,Frozen,etc which could indicate that
b)Customer 2 which the customer id is 54 and we can see that the Fresh is having high score than
c)Customer 3 which the customer id is 271 and we can see that the Milk is having high score indi
```

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 [5]: from sklearn.cross_validation import train_test_split
        from sklearn.tree import DecisionTreeRegressor
        # TODO: Make a copy of the DataFrame, using the 'drop' function to drop the given featur
        new_data = data.drop(['Detergents_Paper'],axis=1,inplace=False)
        # TODO: Split the data into training and testing sets(0.25) using the given feature as t
        # Set a random state.
        X_train, X_test, y_train, y_test = train_test_split(new_data,data['Detergents_Paper'],te

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

```
regressor = DecisionTreeRegressor(random_state=0)
model=regressor.fit(X_train,y_train)
# TODO: Report the score of the prediction using the testing set
score = regressor.score(X_test,y_test)
print(score)
```

```
0.728655181254
```

```
/opt/conda/lib/python3.6/site-packages/sklearn/cross_validation.py:41: DeprecationWarning: This
  "This module will be removed in 0.20.", DeprecationWarning)
```

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:

a)The feature I choose is Detergents_Paper which gave me the highest r2_score when comparing with other category by fitting into the model

b)The reported prediction score is 0.7286%

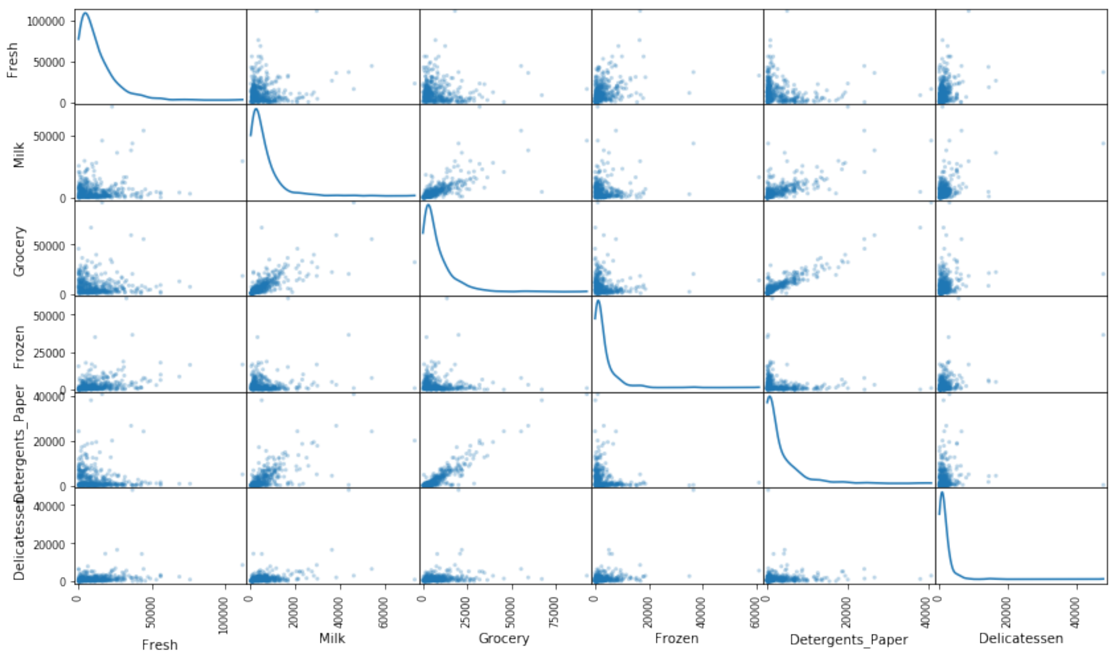
c)I dont think so,this feature will not help us in identifying customer spending habits as it represents as a different category of the customers spending in the Detergents and paper products but leaving out other categories. This is not perfect solution/output where the model can predict the customer spending habits.

1.4.5 Visualize Feature Distributions

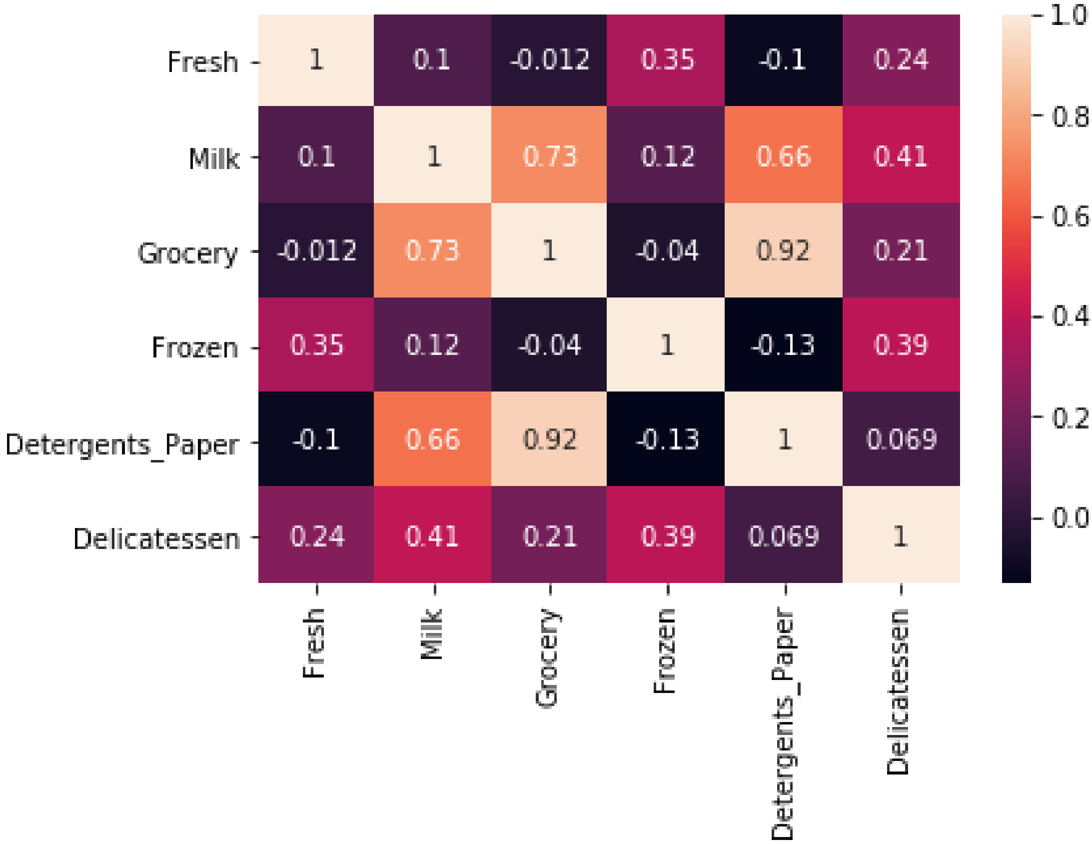
To get a better understanding of the dataset, we can construct a scatter matrix of each of the six product features present in the data. If you found that the feature you attempted to predict above is relevant for identifying a specific customer, then the scatter matrix below may not show any correlation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

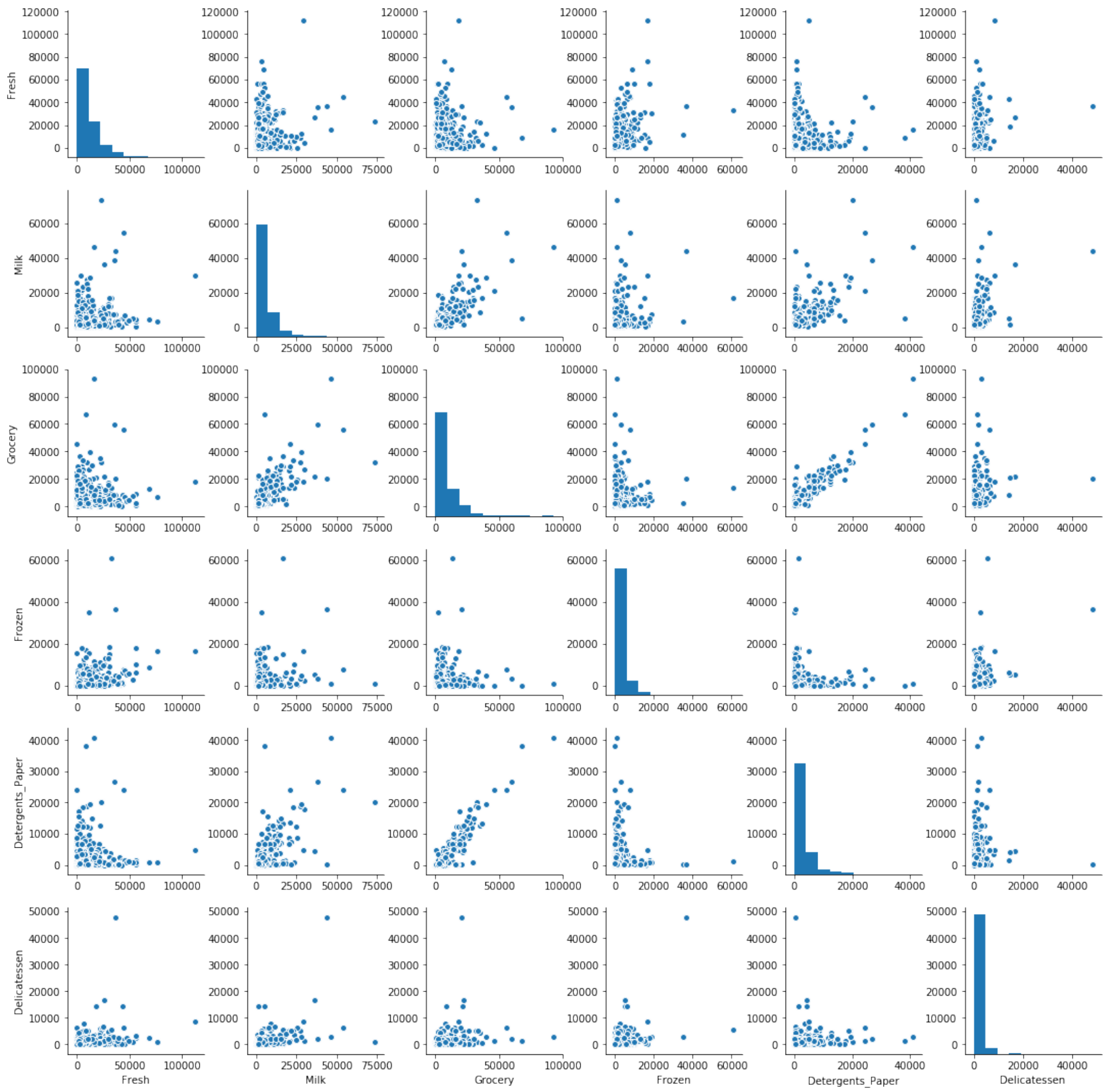
```
In [6]: # Produce a scatter matrix for each pair of features in the data
        pd.scatter_matrix(data, alpha = 0.3, figsize = (14,8), diagonal = 'kde');
```

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




```
In [7]: import seaborn
        seaborn.heatmap(data.corr(),annot=True)
        seaborn.pairplot(data)

Out[7]: <seaborn.axisgrid.PairGrid at 0x7f8fbd9e8a20>
```


Fresh
Milk
Grocery
Frozen
Detergents_Paper
Delicatessen
1
0.1
-0.012
0.35
-0.1
0.24
0.1
1
0.73
0.12
0.66
0.41
-0.012
0.73
1
-0.04
0.92
0.21
0.35
0.12
-0.04
1
-0.13
0.39
-0.1
0.66
0.92
-0.13
1
0.069
0.24
0.41
0.21
0.39
0.069
1
1.0
0.8
0.6
0.4
0.2
0.0



1.4.6 Question 3

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

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

Answer:

a)The distrubution of the dataset is not proper and it is particaulrly towards the origin with few data points far from the origin and by this the degree of correlation between the features are not proper.

b)There are pairs which exhibit the degree of correlation:- The degree of correlation shows the maximum when the pairs are same together and score is 1.0 The degree of correlation between Detergents_Paper and Grocery have the maximum score of 0.92. Another maximum of degree of correlation shows between Grocery and Milk which have the score of 0.73 Between Milk and detergents_paper also have the pretty good degree of correlation and the score is 0.66

c)The Fresh,Milk and Grocery category have the most important datsets that carry the information about the customers behaviour and where they will spend the most whereas Detergents_Paper have the weak revelance which makes it difficult to backup the data and depending upon the category the profile of the data can be identified.

d)The distribution for the points seem highly skewed towards the origin and can be done by doing log function conversions that will distrubute the data evenly.

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.

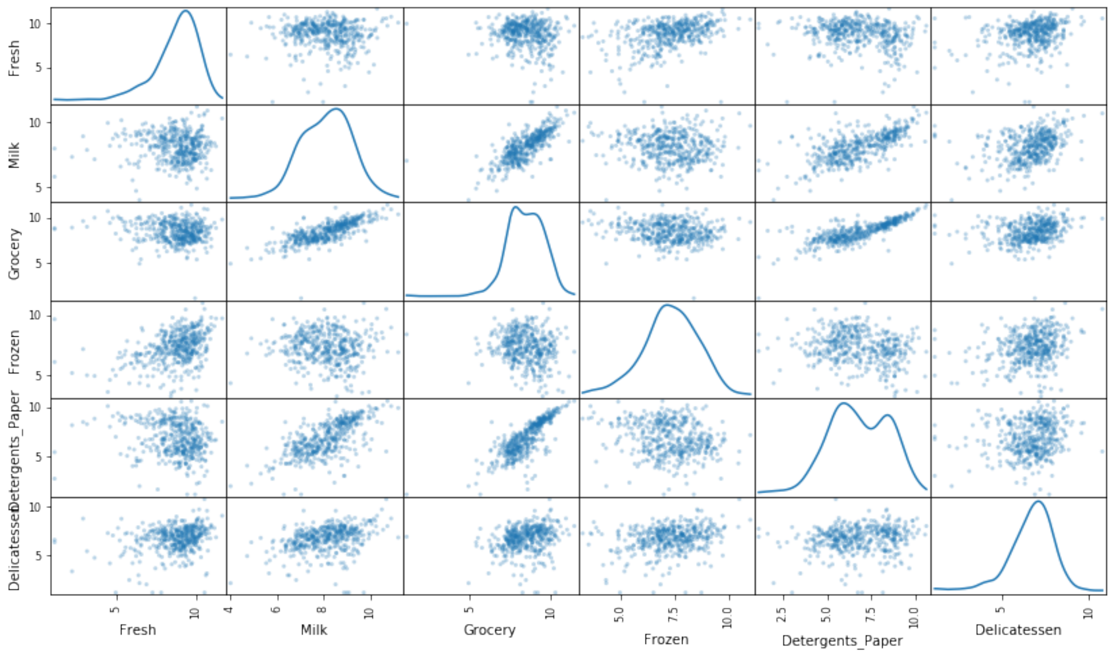
In the code block below, you will need to implement the following: - Assign a copy of the data to `log_data` after applying logarithmic scaling. Use the `np.log` function for this. - Assign a copy of the sample data to `log_samples` after applying logarithmic scaling. Again, use `np.log`.

```
In [8]: # 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)
        print(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');
```

```
      Fresh      Milk   Grocery    Frozen  Detergents_Paper  Delicatessen
0  8.321908  9.927399  10.164197  7.054450          9.059982      8.557567
```

```
1  10.215704  7.278629   7.574045  7.798113          5.318120       7.195187
2   7.641564  8.518592   7.354362  7.021084          4.990433       7.346010
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:9: FutureWarning: pandas.scatter_ma
  if __name__ == '__main__':
```



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

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
0	8.321908	9.927399	10.164197	7.054450	9.059982	8.557567
1	10.215704	7.278629	7.574045	7.798113	5.318120	7.195187
2	7.641564	8.518592	7.354362	7.021084	4.990433	7.346010

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
             print(step)

             # 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  = [65,66,154,75]

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

```
2.53350786861
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

```
2.31824827282
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

```
2.3988562138
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

```
2.34932750101
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
```

```
4.08935876094
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
```

```
2.24228065442
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: a)Yes there are many outliers for more than one feature which are as follows:-

65: An outlier for Frozen and Fresh 66: An outlier for Delicatessen and Fresh 154: An outlier for Delicatessen, Milk and Grocery. 75: An outlier for Detergents_Paper and Grocery.

b)Yes,these outliers data points should be removed.

c)All of these data points were added to the outliers list they fall out of range and are very different to the 'samples' we picked earlier. An algorithm like PCA might end up removing them anyway,go for the simplest solution and trust the Tukey's Method completely.

1.6 Feature Transformation

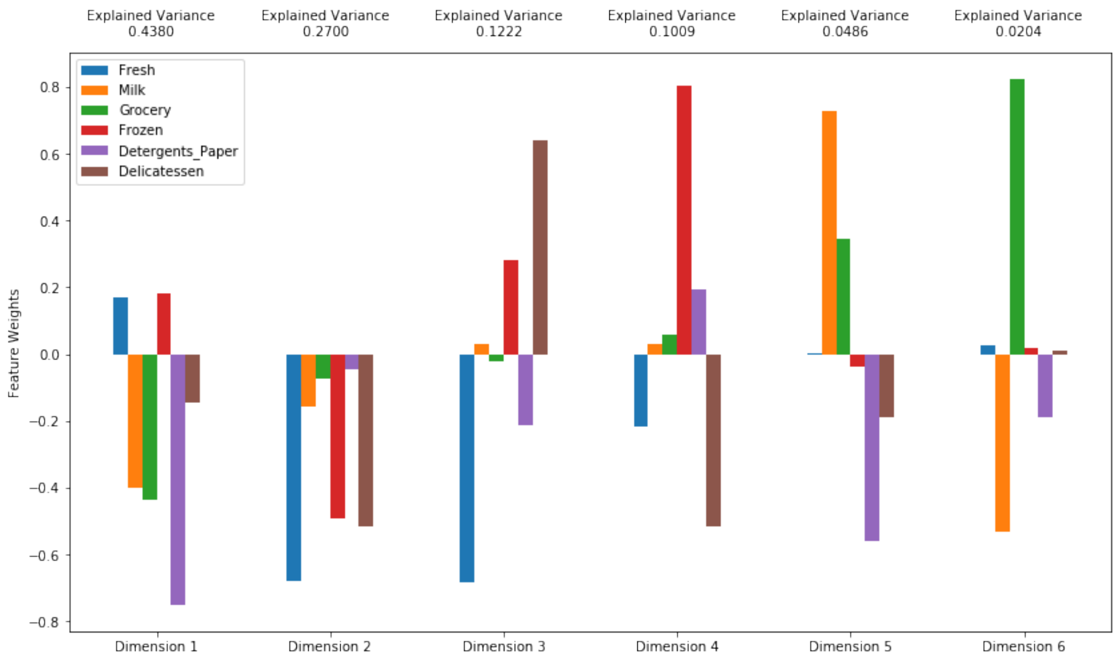
In this section you will use principal component analysis (PCA) to draw conclusions about the underlying structure of the wholesale customer data. Since using PCA on a dataset calculates the dimensions which best maximize variance, we will find which compound combinations of features best describe customers.

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()
         pca_fit=pca.fit(good_data)

         # TODO: Transform log_samples using the PCA fit above
         pca_samples=pca_fit.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:

a)First two Components:- First PCA:-44.24% Second PCA:-27.66% Total:-71.90%

b)First Four Components:- First PCA:-44.24% Second PCA:-27.66% Third PCA:-11.62% Fourth PCA:-9.62% Total:-93.14%

c)The variance of the data by the first four principal Components are as follows:-

```
First Component:-
    As we can observe that Fresh and Frozen have the positive feature weight indicating that the

Second Component:-
    Every category in this featuere is all negative feature weight as a result it will predicts

Third Component:-
```

```
    In this Component we can very easily say that the customer runs the Delicate Shop where all

Fourth Component:-
    In this Component we can say that the customer runs the small grocery shop where the custome
```

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]:
```python
# 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      -3.5614      -1.0536       0.9521      -0.4955       0.2783
1       2.1028      -1.2227      -0.2183      -0.5592      -0.2072
2       1.3455       0.6596       1.5260      -0.7475       0.7974

   Dimension 6
0       0.0275
1       0.0536
2      -0.8079
```

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.

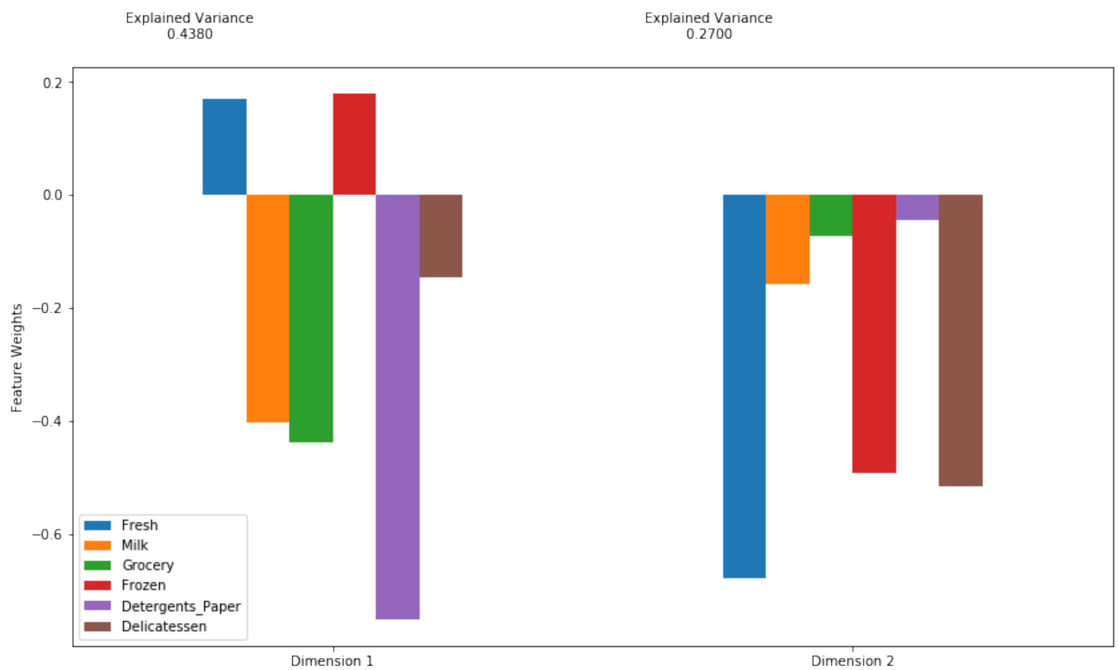
In the code block below, you will need to implement the following: - Assign the results of fitting PCA in two dimensions with `good_data` to `pca`. - Apply a PCA transformation of `good_data` using `pca.transform`, and assign the results to `reduced_data`. - Apply a PCA transformation of `log_samples`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

In [13]:
```python
from sklearn.decomposition import PCA
# TODO: Apply PCA by fitting the good data with only two dimensions
pca = PCA(n_components=2)
pca_fit=pca.fit(good_data)

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

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

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

Out[13]:

```
             Explained Variance   Fresh    Milk  Grocery  Frozen  \
Dimension 1               0.438  0.1709 -0.4012  -0.4377  0.1805
Dimension 2               0.270 -0.6775 -0.1584  -0.0725 -0.4917

             Detergents_Paper  Delicatessen
Dimension 1           -0.7512       -0.1460
Dimension 2           -0.0450       -0.5166
```



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	-3.5614	-1.0536
1	2.1028	-1.2227
2	1.3455	0.6596

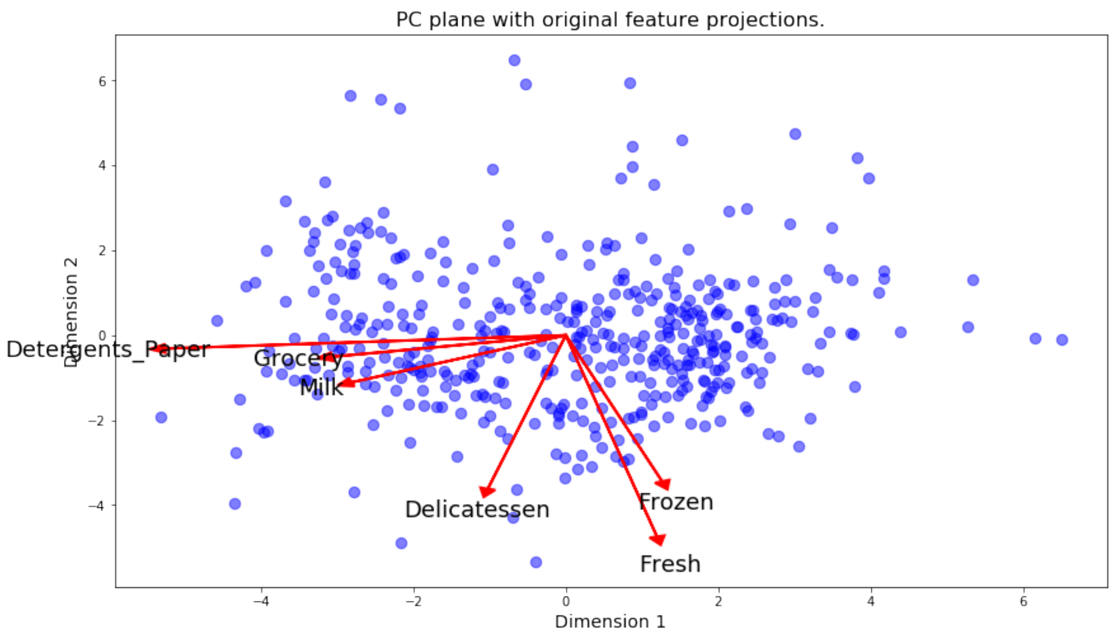
1.7 Visualizing a Biplot

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 0x7f8fb4ffbb00>
```



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:

a)The adavantages of K-Mean Clustering Algorithm are as follows:- It is easy implementation and perofrms high performance for the specific dataset.It performs very efficient in large datasets and also that it has parameters to find the clustering which are mean and varaince where clusters are seperable and non-uniformity.

b)The advanataged of Guassian Mixture Model Clustering Algorithm are as follows:- This algortihm is also esy implementation and performs high performance which is much better than K-Means Clustering. Well it have more parameters that are means,variance,pi and sigma. Moreover,this type of clustering is soft clustering and datasets do not necessary have to be assigned rigidity and with lower probabilities could be assigned with multiple clusters at once.It is able to predict the probabilities events rather than rigid features.

c)I would go for Guassian Mixtire Model for this type of dataset because the dataset is uniform according to the scatter plot and pca_results which have given the idea about the cutomers spending on the particular category.

1.8.2 Implementation: Creating Clusters

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

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

```
In [16]: from sklearn.mixture import GMM
         from sklearn.metrics import silhouette_score

         #TODO: Apply your clustering algorithm of choice to the reduced data
```

```python
clusterer = GMM(n_components=3,random_state=0)
clusterer.fit(reduced_data)

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

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

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

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

```
0.375850993734
```

```
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:58: DeprecationWarning: Clas
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
```

```
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/deprecation.py:77: DeprecationWarning: Func
  warnings.warn(msg, category=DeprecationWarning)
```

Answer:

a) noc Silhouette Score 2 0.316017 3 0.375223 4 0.339344 5 0.312026 6 0.269277 7 0.320230 8 0.308761 9 0.303447 10 0.314744 11 0.291038 12 0.258313 13 0.208156 14 0.213800 15 0.245388 16 0.176322 17 0.144191 18 0.196488 19 0.197134

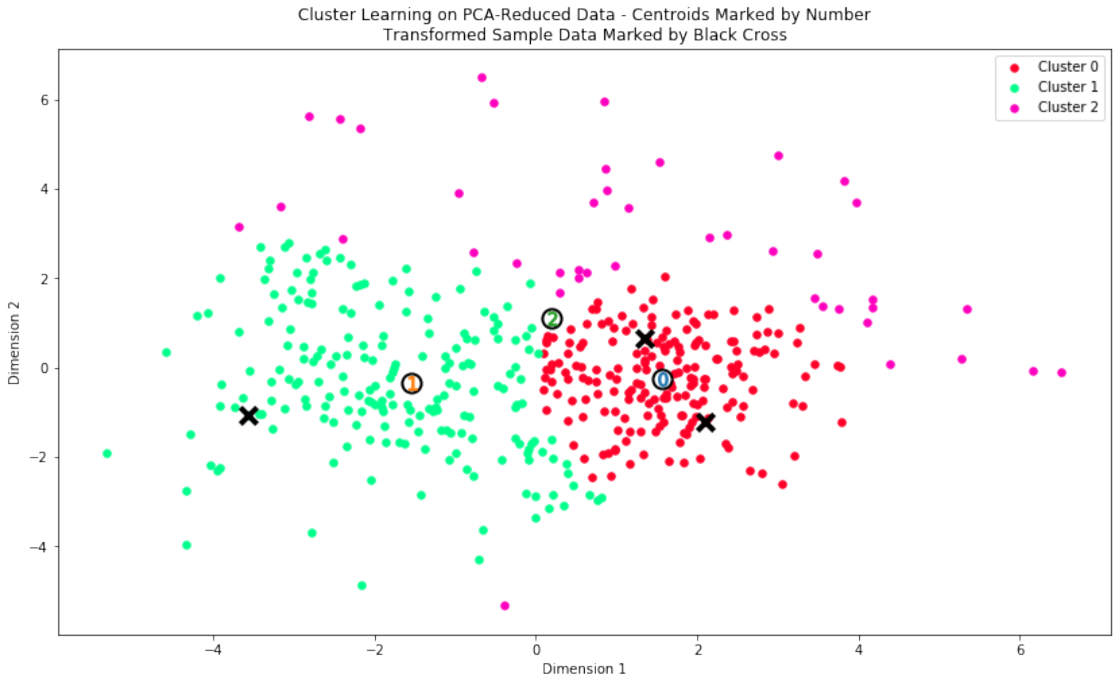
   noc is number of components

b)The best silhouette score is 0.375223 where the number of components is 3

1.8.3 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)
```



1.8.4 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.

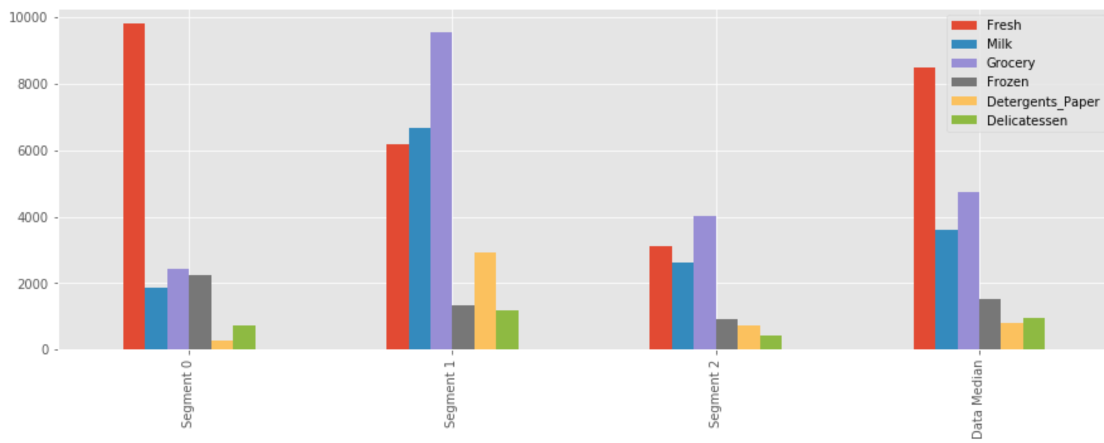
In the code block below, you will need to implement the following: - Apply the inverse transform to `centers` using `pca.inverse_transform` and assign the new centers to `log_centers`. - Apply the inverse function of `np.log` to `log_centers` using `np.exp` and assign the true centers to `true_centers`.

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  9802.0  1882.0   2419.0  2257.0              279.0         719.0
Segment 1  6184.0  6684.0   9540.0  1354.0             2919.0        1198.0
Segment 2  3118.0  2641.0   4007.0   909.0              739.0         439.0
```

```
In [19]: import matplotlib.pyplot as plt
         import seaborn as sns

         segment_samples=true_centers.copy()
         segment_samples.loc[segment_samples.shape[0]]=data.median()

         plt.style.use('ggplot')
         segment_samples.plot(kind='bar',figsize=(15,5))
         labels = true_centers.index.values.tolist()
         labels.append('Data Median')
         plt.xticks(range(segment_samples.shape[0]),labels)
         plt.show()
```



1.8.5 Question 8

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

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

Answer:

Cluster 0 is Grocery and Retail Store Cluster 1 is Hotel/Cafe

Segment 0 belongs to cluster 1 This Segment 0 indicates that the customer runs the Hotel and Cafe where the Fresh Category have the maximum score followed by Grocery,Milk and Frozen.

Segement 1 belongs to cluster 0 This Segment 1 indicates that the customer runs the Retail/Grocery Store or maybe retail store where you can observe that the Grocery category have the maximum score which then followed by the Milk and Fresh category that have the maximum scores where there is a minor difference between them which is even further followed by Detergents_Paper and Delicatessen.

Segment 2 belongs to cluster 0 This Segment 2 indicates that the customer runs the small Grocery Store just like the family owned shop buying quantities at the very low compared to the Retail Store which buys at the large quantities as we have seen at Cluster/Segment 0

1.8.6 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 [22]: # Display the predictions
         for i, pred in enumerate(sample_preds):
             print("Sample point", i, "predicted to be in Cluster", pred)
```

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

Answer:

Segment 0 Predicted:-Grocery Store/Retail Store Model:-Grocery Store/Retail Store The model have got the right prediction as the customer runs the Grocery Store/Retail Store and i have predicted due to high values in Grocery,Milk and Fresh

Segment 1 predicted:-Hotel and Cafe model:-Hotel/Restaurant/Cafe The model have got the right prediction again as the customer runs either Vegan/Non-Vegan Restaurant or Cafe and i have predicted due to high values in Fresh,Grocery and Frozen

Segement 2 predicted:-Small Grocery Store Model:-Grocery/Retail Store The model have predicted that the segment or the sample point belong to Grocery/Retail Store but the model does not know that the sample point is the retail store or small grocery store

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:

The model has established two main customer types - Cluster 1 'supermarkets'/'bulk distributors' (who stock lots of different items) and Cluster 0 'restaurants/cafes' who stock fresh food.

It is likely that customers from Cluster 0 who serve lots of fresh food are going to want 5-day weeks in order to keep food as fresh as possible

Cluster 1 as they buy a more wide variety of goods so do not necessarily need a daily delivery.

The Company could run A/B tests and generalize. By picking a subset customers from each Cluster, they can evaluate feedback seperately.

Customers at the supermakets/bulk dsitrubutors requires a lot of fresh and milk items rather than the grocery or frozen items where they can keep it for days or months or years as the supermarkets and it depends upon the customers who are daily buyer of fresh and milk will be happy or not when the delievery service is changed from 5 days a week to 3 days a week.

It allows a business to make educated and targeted decisions that would benefit their customers going forward depending on their profile.

Acoording to my opinion,the system should not be implemented.

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:

By first running an unsupervised clustering approach, such as GMM, we first establish clusters and use this as a new feature - which cluster they are in. We can call this feature 'Customer Segment', and they could be assigned abritrary enumerated values e.g. 0 and 1 for this worksheet. We'd then create new data points for each new customer, with all of their spending estimates. We can then use a Supervised learning technique, for example a Support Vector Machine (which does very well to seperate classified clusters) with a target variable of 'Customer Segment' Standard

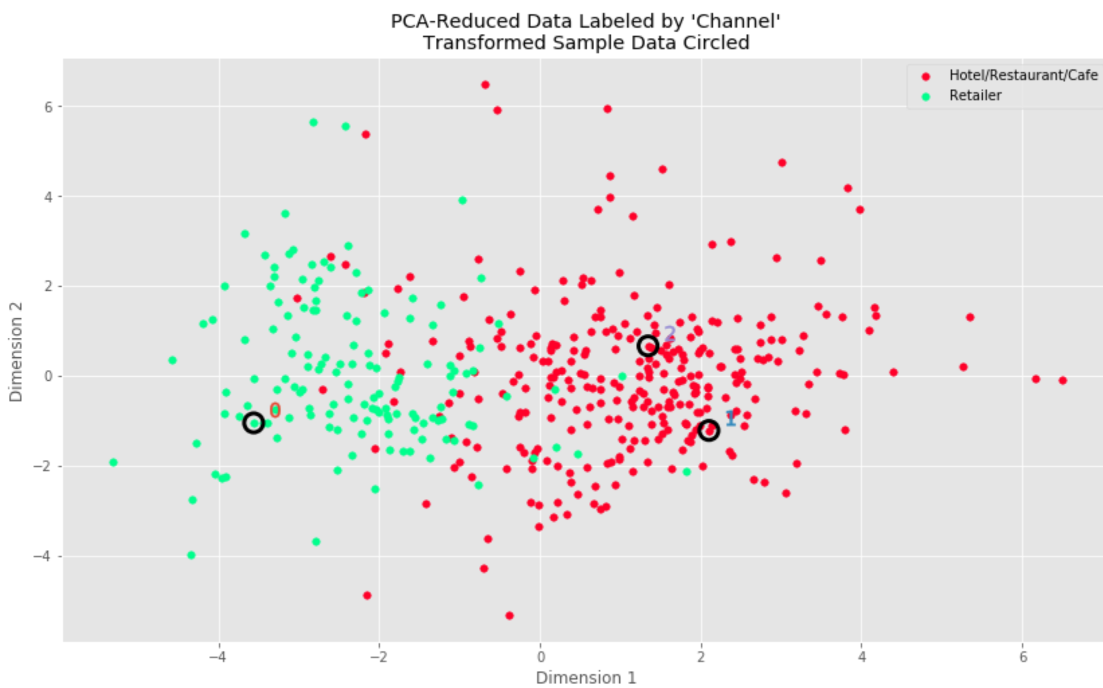
Supervised Learning optimizations could be used to tune the model - boosting, cross-validation ,grid search cv,etc

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: a)The clustering algorithm is GMM and the number of clusters was compared with the score in order to get the best one.The clustering algorithm was able to identify the relationship as well but clustering algorithm was pretty sure regarding the customer segments or cluster in which they belong as each data points in the category have been seperately laid out specifying in its own way and can tell at which cluster it belongs to.

b)The dataset which have been provided is uniform distrubution among the categories where the data points are braodly are classified into many other categories which are Delicatessen and the shops can be fragile shops,etc rather purely classified into restaurants or retailers.The distrubution have well defined seperation between the clusters.

c)Yes, they are almost exactly the same prediction - Cluster 0 I thought to be Retailers/Grocery Store,Cluster 1 being Restaurants/Cafes except for cluster 2.

> **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.