#Machine Learning Engineer Nanodegree

##Project 3: Creating Customer Segments

###Introduction

This documents presents the results for the third project within the Machine Learning Engineer Nanodegree program. This assessment required the student to apply dimensionality reduction and classification techniques to a set of sales data from a wholesale grocery distributor, in order to categorize its customers into segments.

###Data

```
Table 1: Raw Dataset (first 5 records)
```

Out[6]:

	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

```
Dataset rows: 440
Dataset columns: 6
```

This assessment uses data provided via the Udacity platform. The dataset has 440 rows and 6 columns.

###Question 1

Before doing any computations, what do you think will show up in your computations? List one or two ideas for what might show up as the first PCA dimensions, or what type of vectors will show up as ICA dimensions.

####Answer

Under the PCA method, the first dimension will show the global direction of the data (maximum variance). According the dataset variance's shown below, it may be reasonable to suggest that the first component will carry a high load of the 'Fresh' feature since it has the highest variance.

```
Table 2: Raw Dataset Statistics
```

Out[8]:

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicatessen
std dev	12647.329	7380.377	9503.163	4854.673	4767.854	2820.106

ICA instead finds subcomponents according to which are statistically independent. Under this premise, it may be reasonable to suggest that the ICA method may also find 'Fresh' to be one of its components, however it is difficult to say which remaining components it would select as the components need not be orthogonal in the feature space, as opposed to PCA.

###Question 2

How quickly does the variance drop off by dimension? If you were to use PCA on this dataset, how many dimensions would you choose for your analysis? Why?

####Answer

PCA combines features in order to create a set of composite features with minimal information loss. By doing so, we can reduce the feature set to those which are able to best explain the wider dataset. PCA does this by projecting each data point to the line of largest variance, retaining those data with the greatest variance. PCA then orders its component output in terms of explained variance, that is, the fraction of variance in the data explained by each principle component. As such, the first component will explain the most variance, followed by the second component and so forth.

Fit PCA.

```
Out[9]:  PCA(copy=True, n_components=6, whiten=False)
```

Show PCA components.

```
Table 3: PCA Components
```

```
Out[10]:
```

	fresh	milk	grocery	frozen	detergentspaper	delicatessen
0	-0.977	-0.121	-0.062	-0.152	0.007	-0.068
1	-0.111	0.516	0.765	-0.019	0.365	0.057
2	-0.179	0.510	-0.276	0.714	-0.204	0.283
3	-0.042	-0.646	0.375	0.646	0.149	-0.020
4	0.016	0.203	-0.160	0.220	0.208	-0.917
5	-0.016	0.033	0.411	-0.013	-0.871	-0.265

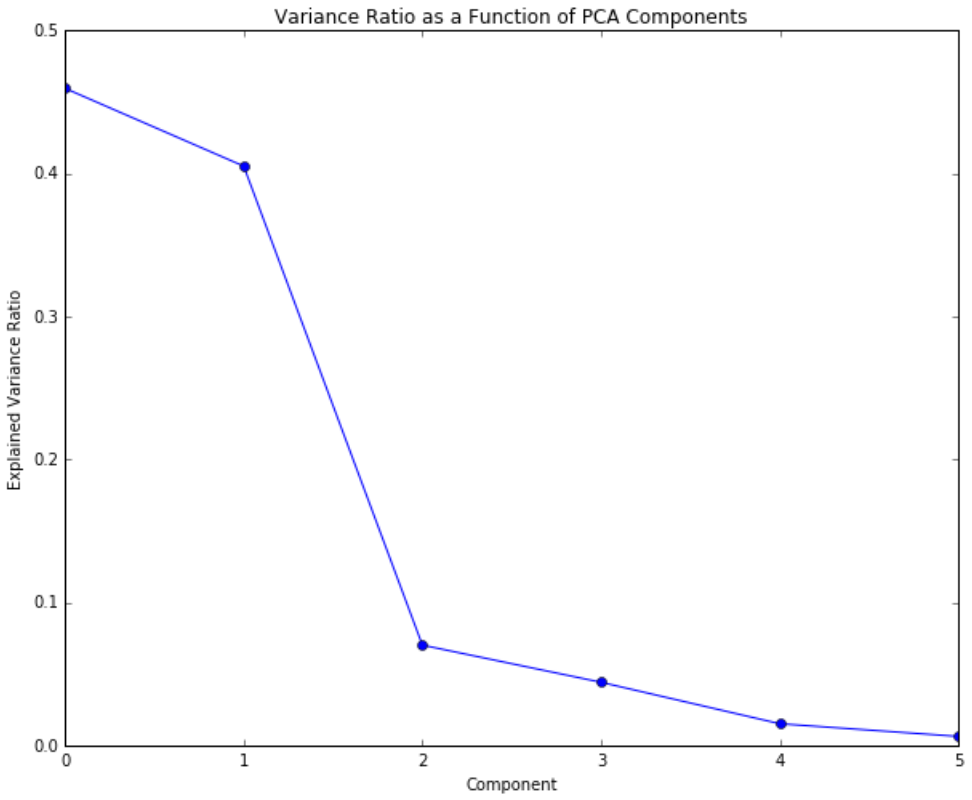
Calculate PCA dimensions.

```
Table 4: PCA Dimensions
```

```
Out[12]:
```

	dimension1	dimension2	dimension3	dimension4	dimension5	dimension6
0	0.46	0.405	0.07	0.044	0.015	0.006

Plot the expected variance ratio for each component.



The variance ratio of the first two dimensions are 0.4596 and 0.4052 respectively, resulting in 0.8648 of the variance being along the first two dimensions. The variance along the third dimension is only 0.0700, which is a 0.1728 drop relative to the second dimension. We should therefore keep only the first two dimensions for our analysis. This will help to avoid the curse of dimensionality.

Interpreting these results allows us to form an initial impression about the customer segments contained in the data. One possibility could be that many customers are able to be split into customers ordering mainly 'Fresh' items versus customers ordering ordering 'Grocery', 'Milk' and 'Detergents'.

###Question 3

What do the dimensions seem to represent? How can you use this information?

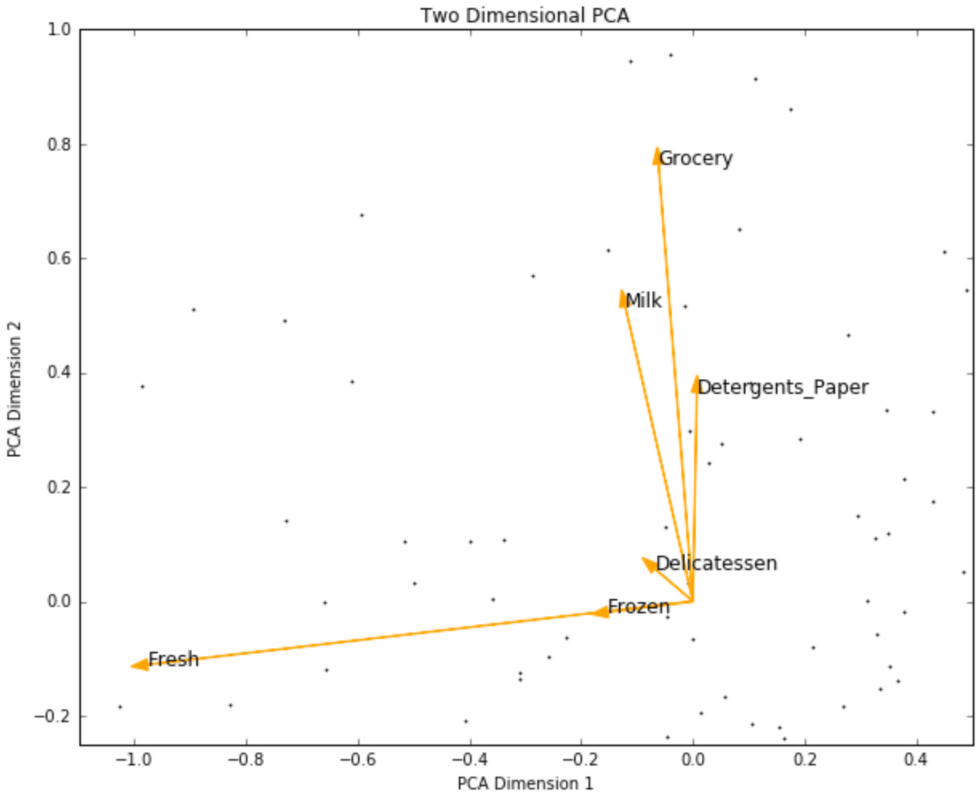
####Answer

These dimensions are linear combinations of the datasets five features. We can read off these linear combinations from the pca component array shown above.

Observing the first row, we see that the first dimension is almost completely (anti-) aligned along the 'Fresh' direction (-0.9765) and slightly in the 'Milk' direction (-0.1212) and the 'Frozen' direction (-0.1524). It is almost orthogonal to the other directions. Note however, although these features are (anti-) aligned over this dimension, the prevalence of that feature in the component is represented in terms of absolute magnitude and changing the signs of the components, does not change the variance. As such, we can make the statement that the first dimension contains data mostly on 'Fresh' foods, and to a lessor extent, 'Milk' and 'Frozen' foods.

Observing the second row, we see that the second dimension is most strongly aligned in the 'Grocery' direction (0.7646) followed by the 'Milk' direction (0.5158) and 'Detergents_paper' direction (0.3654), and slightly in the 'Fresh' direction (-0.1106). It is almost orthogonal to the other directions. Therefore, the second dimension contains data mostly on 'Grocery', 'Milk', and to a lessor extent, 'Detergents_paper'.

Below shows a plot of the first two PCA dimensions discussed above.



PCA allows us to reduce the dimensions of the data whilst maintaining most of the information. In this way, PCA allows us to make an assessment of which variables matter the most as we progress to building our classification model. From the plot above, we can see that over these dimensions, 'Fresh', 'Milk' and 'Grocery' are the highest uncorrelated components.

###Question 4

For each vector in the ICA decomposition, write a sentence or two explaining what sort of object or property it corresponds to. What could these components be used for?

####Answer

Within each vector of the ICA, the magnitude of each features coefficient provides insights as to how important that feature is to that ICA vector. By focusing on those coefficients which have the greatest magnitude within each vector, we are able to gain insights as to how customers purchase products within each feature group. If two coefficients have the same sign, then those features tend to trend together, implying that customers tend to purchase these items together. Whilst, if two coefficients have the opposite sign, it implies that customers who buy more of one item, tend to buy less of the other.

Fit ICA.

```
Out[16]: FastICA(algorithm='parallel', fun='logcosh', fun_args=None, max_iter=200,
             n_components=6, random_state=None, tol=0.0001, w_init=None,
             whiten=True)
```

Show ICA components.

```
Table 5: ICA Components (10^5)
```

Out[17]:

	fresh	milk	grocery	frozen	detergentspaper	delicatessen
0	-0.396	0.095	0.047	0.071	-0.160	0.103
1	0.030	-0.104	-1.365	0.132	2.778	0.538
2	-0.039	-0.031	-0.061	-0.053	0.044	1.818
3	-0.022	0.699	-0.527	-0.076	-0.460	-0.332
4	-0.034	-0.746	0.252	0.008	-0.401	0.536
5	-0.086	-0.019	0.087	1.115	-0.060	-0.594

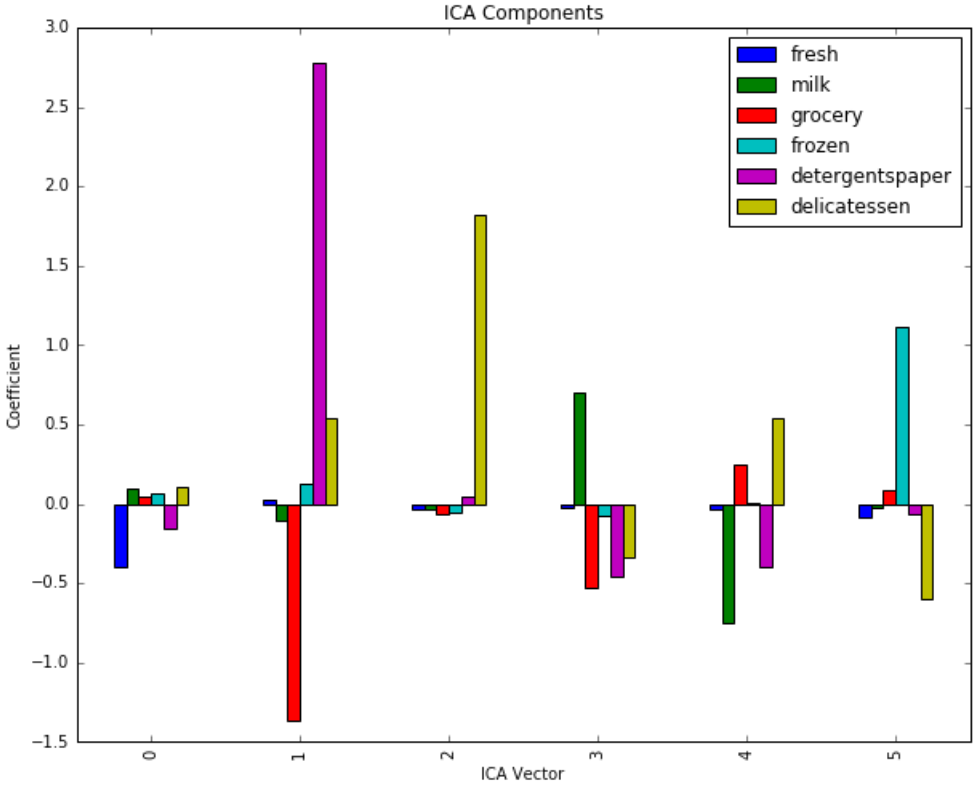
Observing the first row, we see that the first vector has a high representation of the 'Fresh' feature, with a coefficient of -0.3965. The other features have weaker representation on the first dimension. However, noting the polarity of each coefficient over this vector, we can make the assessment that customers represented by this vector tend to purchase 'Fresh' and 'Detergentspaper' products together, and 'Milk', 'Frozen' and 'Delicatessen' products together.

Observing the second row, we see that the second vector has a high representation of both 'Grocery' and 'Detergents paper', however the coefficients of each are of different polarity (-1.3651 and 2.7780 respectively). This indicates that, with all else held equal, high spending in 'Grocery' is associated with low spending in 'Detergents paper', and visa versa. We can also make the assessment that customers represented by this vector tend to purchase 'Milk' and 'Grocery' products together, and 'Fresh', 'Frozen', 'Detergentspaper' and 'Delicatessen' products together.

Observing the third row, we see that the third vector has a high representation of the 'Delicatessen' feature, with a negative coefficient of 1.8180. Indicating low spending on this feature within the vector. Customers represented by this vector tend to purchase 'Fresh', 'Milk', 'Frozen' and 'Grocery' products together.

Finally, observing the forth row, we see that the forth vector has a high representation of the 'Milk' feature, with a positive coefficient of 0.6986. Indicating high spending on this feature within the vector. Customers represented by this vector tend to purchase 'Fresh', 'Frozen', 'Detergentspaper', 'Delicatessen' and 'Grocery' products together.

Below shows a plot of each vector of the ICA.



As described above, interpreting these results allows us to form an initial impression about the customer segments contained in the data by providing insights as to their purchasing behavior.

###Question 5

What are the advantages of using K Means clustering or Gaussian Mixture Models?

####Answer

Gaussian Mixture Models (GMMs) make a probabilistic assignment of points to classes, whereas K Means makes a deterministic assignment.

An advantage of GMMs is that prior uncertainty about the assignment of a point to a cluster can be inherently reflected in the probabilistic model (soft assignment). Therefore, a GMM would be more suitable if the underlying dataset is a representation of a mixture of Gaussians. Alternatively, if cluster assignments are expected to be deterministic, a K Means clustering algorithm has advantages.

It is worth noting, when assessing computation speed, the EM algorithm with Gaussian mixtures is generally slightly slower than Lloyd's algorithm for K Means, since computing the normal probability (EM) is generally slower than computing the L2-norm (K Means).

Since there is nothing to suggest that this data has been formed from a mixture of normals, and the goal of this assessment is to discretely characterise customers (not to assign probabilities), K Means would be a more suitable algorithm to apply.

###Question 6

Generate a cluster visualization of the data.

####Answer

Fit PCA with two components.

```
Out[20]: PCA(copy=True, n_components=2, whiten=False)
```

Use PCA to transform the data under tw o components.

```
Table 6: PCA Reduced Data (first 5 records)
```

Out[21]:

	component1	component2
0	-650.022	1585.519
1	4426.805	4042.452
2	4841.999	2578.762
3	-990.346	-6279.806
4	-10657.999	-2159.726

Fit KMeans clustering algorithm w ith five clusters to the PCA reduced dataset.

```
Out[22]: KMeans(copy_x=True, init='k-means++', max_iter=300, n_clusters=5, n_init=10,
             n_jobs=1, precompute_distances='auto', random_state=None, tol=0.0001,
             verbose=0)
```

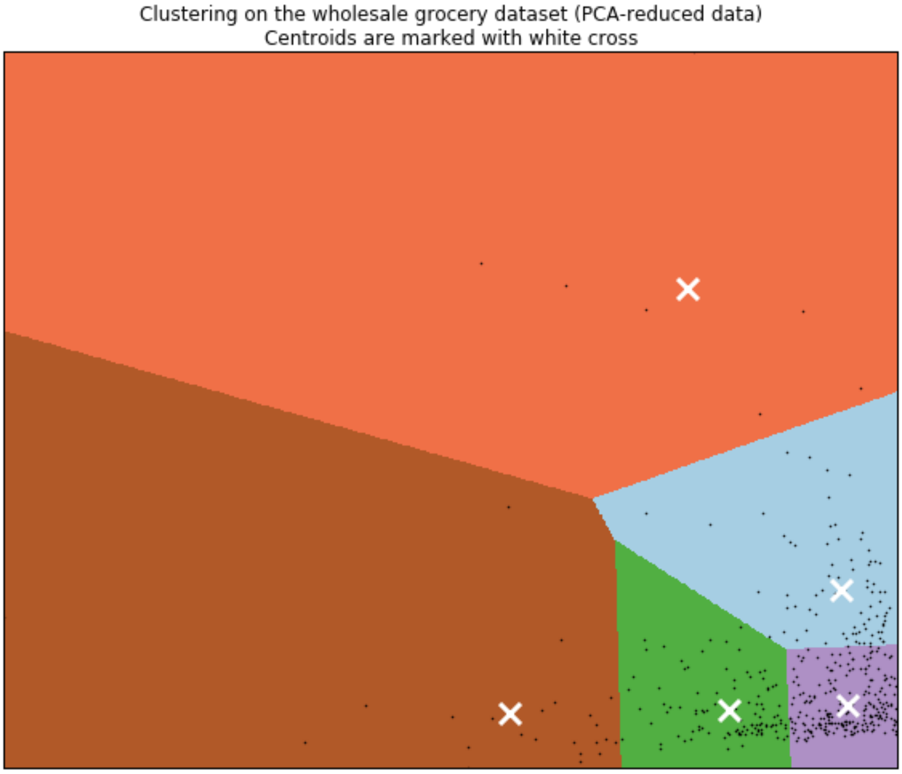
Find the centroids for KMeans clusters.

```
Table 7: Centoids for KMeans
```

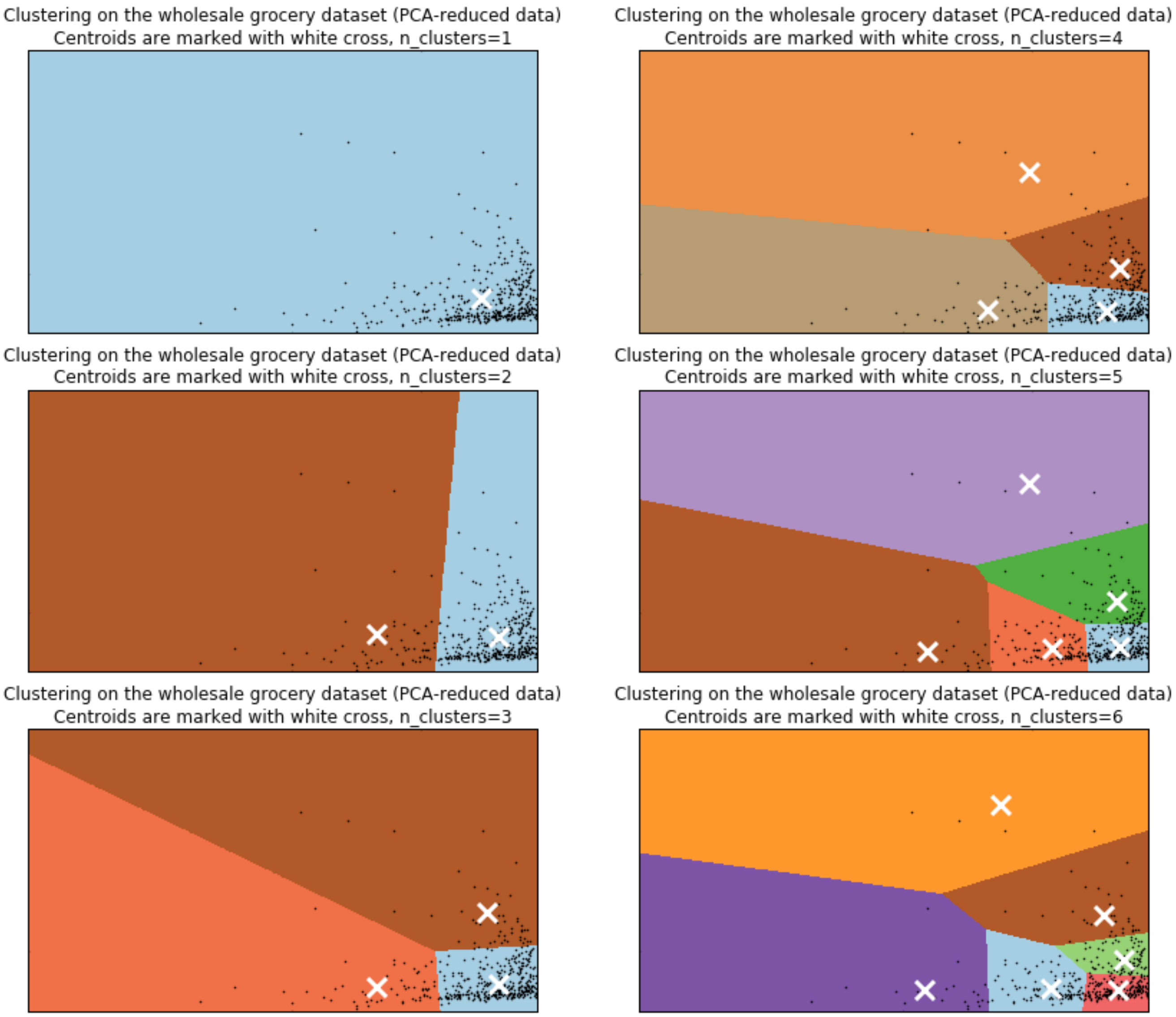
Out[23]:

	component1	component2
0	6399.712	-4169.297
1	-9052.400	-4808.559
2	5607.917	14199.180
3	-37704.642	-5488.354
4	-14537.718	61715.671

Plot the KMeans clusters w ith centoids over the PCA reduced dataset.



We can also plot the KMeans clusters with centoids with a variable cluster number. See the plot below for a cluster size ranging from one to six.



The choice of three clusters seems to generally categorize the data, however choice of five clusters seems to a better job of classifying the tight cluster where the bulk of datapoints lie.

###Question 7

What are the central objects in each cluster? Describe them as customers.

####Answer

Convert centroids back to original space.

```
Table 8: Converted Centroids
```

Out[26]:

	fresh	milk	grocery	frozen	detergentspaper	delicatessen	total
0	21796.211	4511.413	4925.148	4607.261	1089.284	1902.087	38831.404
1	4278.491	8251.415	12438.315	1857.691	5287.207	1404.009	33517.128
2	6737.047	2123.431	3219.601	2259.084	840.623	788.315	15968.101
3	24860.692	43833.949	61861.063	4977.669	27876.759	6880.809	170290.941
4	50021.119	7719.092	6274.136	9011.881	682.366	3834.436	77543.030
5	6593.445	17979.749	26340.779	2192.765	11770.138	2720.671	67597.547

These converted centoids can be used to represent five classified customer segments, along with their expenses under each feature.

Observing the first row, we see that the first customer spends the most on 'Fresh', followed by 'Grocery', 21796.2108 and 4925.1482 respectively. The same customer spends the least on 'Delicatessen', 1902.0868. This customer has the lowest spend of all five customer segments.

Observing the second row, we see that the second customer spends the most on 'Fresh', followed by 'Grocery', 4278.4906 and 12438.3153 respectively. The same customer spends the least on 'Detergents Paper', 5287.2075. This customer has the second highest spend of all five customer segments.

Observing the third row, we see that the third customer spends the most on 'Grocery', followed by 'Milk'. Observing the fourth row, we see that the fourth customer spends the most on 'Frozen', followed by 'Fresh'. And finally, observing the fifth row, we see that the fifth customer spends the most on 'Milk' followed by 'Detergents Paper'.

###Question 8

Which of these techniques did you feel gave you the most insight into the data?

####Answer

The PCA data reduction technique in combination with K-means-clustering technique provided the most insight into the data. The PCA reduction technique was able to reduce the six features of the original dataset according to two components which maximize variance. This enabled the data to be clustered within a 2-dimensional space using a K-means-clustering technique.

By clustering the data and forming a number of customer segments, the client can now better disaggregate their customers by spending behaviour. Follow on analysis may attempt to draw relationships between spending behaviors of these customer segments. For example, of those customers who have a high total spend, which type of product do they spend the most on?

###Question 9

How would you use that technique to help the company design new experiments?

####Answer

If the client had plans to introduce or retire delivery strategies in the future, he or she could use the customer segmentation provided by the K-means technique in order to focus efforts on that specific segment. For example, the client could test whether a change in delivery strategy was able to shift item preferences for low spending customer segments from one particular item to another. The ability to understand preferences of each customer segment can help drive customer delivery experiences and ultimately improve customer experience.

###Question 10

How would you use that data to help you predict future customer needs?

####Answer

The client could for example, monitor changes in the spending behavior of each of these identified customer segments, and potentially introduce supervised learning techniques in order to predict changes in product demand. Doing so would provide the client with a competitive advantage in being able to lead changes (i.e. adjust inventories, investment and staff training) which suit shifting customer preferences.