***Question 1: Consider the total purchase cost of each product category and the statistical description of the dataset above for your sample customers. What kind of establishment (customer) could each of the three samples you've chosen represent? Hint: Examples of establishments include places like markets, cafes, and retailers, among many others. Avoid using names for establishments, such as saying "McDonalds" when describing a sample customer as a restaurant.***

Our first example looks like it might be a restaurant or cafe. There is high spend in Fresh (I'm assuming this is produce) and Grocery relative to the other two categories. This sample also spends more in Detergents\_Paper and Delicatessen than three-quarters of our data.<br>

The second sample might be a cafeteria for a school or university. There is low overall spend in Fresh foods compared to the Milk, Grocery, and Delicatessen samples. Additionally, the Frozen and Detergents\_Paper categories have a higher spend than both the other samples. In this case, Grocery and Detergents\_Paper are well beyond the 75th percentile of their spend category.<br>

Lastly, the third would look something more of a Farmer's Market (although I'm not sure if food for famer’s markets run through a warehouse first.) Fresh food represents almost half of the spend for all categories combined and is just about more than three quarters of our data. Milk and Grocery represent the next sizeable categories in spend, but they are not the prominent drivers in total spend.

***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.***

I attempted to predict Detergents\_Paper and the R^2 score was about 0.729. This score is much better than guessing so it can likely be derived from other features. If there are certain spend categories that correlate well to `Detergents\_Paper`, predicting its value is a viable option meaning that it would not be relevant feature. Features that can be derived from other features are not necessarily useful in our analysis.

***Question 3: Are there any pairs of features which exhibit some degree of correlation? Does this confirm or deny your suspicions about the relevance of the feature you attempted to predict? How is the data for those features distributed? Hint: Is the data normally distributed? Where do most of the data points lie?***

We can see that there about three obvious pairs of features that correlate with one another; Grocery and Milk, Detergents\_Paper and Milk, and Grocery and Detergents\_Paper. This does confirm that Detergents\_Paper would not be a relevant feature in our analysis if we have other data that correlates to it. Knowing that these three are all loosely tied to one another, we can predict one category using what we know about the others. On a broader basis, we can group these customers into a segment and/or single feature since the spending habits look to be similar. <br>

The data is skewed right, meaning the average is greater than the median spend amount. It would be important for us to understand what is happening with the customers that are driving that skew since they are the big spenders. Analyzing the accounts that drive the most spend and applying the same methods to most other accounts can help us solve our monetary bleeding faster than focusing on the small spenders first.

***Question 4: Are there any data points considered outliers for more than one feature based on the definition above? Should these data points be removed from the dataset? If any data points were added to the `outliers` list to be removed, explain why.***

Points 65, 66, 75, 128, and 154 are all outliers that occur in two or more of the categories. We will remove all the outliers as they skew the variance in the data. Like we saw earlier, the data is skewed right, so the mean is greater than the median. If the outliers remain, our cluster centers may not be true to most the data and our segment classifications might be off. The PCA will also be affected as the outliers will influence the variance between our features.

***Question 5: How much variance in the data is explained in total by the first and second principal component? What about the first four principal components? Using the visualization provided above, discuss what the first four dimensions best represent in terms of customer spending. Hint: A positive increase in a specific dimension corresponds with an increase of the positive-weighted features and a decrease of the negative-weighted features. The rate of increase or decrease is based on the individual feature weights.***

Components One and Two: `0.7253`<br>

Components One through Four: `0.9280`<br>

The first two components account for about 73% of the variance in our data and the sum of the first four represents about 93% of variance.<br>

Our first dimension shows a strong relation between Milk, Grocery, and Detergents\_Papers and a similar relation with Milk and Frozen. The second dimension is almost the inverse of the first where Milk, Frozen, and this time Delicatessen are the primary drivers of the variance while Milk, Grocery, and Detergents\_Paper are also related but with smaller weights. These two dimensions explain more than half the variance.<br>

Including components three and four helps us explain about 20 points more of the variance in the data. The third component shows a very high weight increase (about 0.75) in Fresh and a 0.20 increase in the Detergents\_Paper. All other features for this component have little change in weight except for Delicatessen’s weight decreasing by about 0.5, pulling it away from all the other features. Lastly, component four shows us that Frozen, Detergents\_Paper, and Delicatessen can explain about 10 points of the variance. Fresh, Milk, and Grocery do not have much influence in the one.

***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?***

<b>K-Means:</b> This clustering algorithm tries to put the data into K groups that equalizes the variance between each other and minimizes the sum-of-squares from the centroid. However, the K-Means algorithm does not accommodate non-uniform shaped clusters very well. (1)

<b>Gaussian Mixture Model:</b> This algorithm is an efficient way to group together data that are not uniform in shape or size. While the K-Means model tries to find an equal variance between groups, a Gaussian Mixture Model will try to capture the shape instead. When we look at the Biplot above we can see that our data will not be completely separable into clusters as the K-Means algorithm will force. "It can also draw confidence ellipsoids for multivariate models"(2). This would allow us to draw boarders with soft boundaries so that points can be represented into multiple groups rather than one or the other. For that reason, we will continue the project using the Gaussian Mixture Model.

(1): <href><http://scikit-learn.org/stable/modules/clustering.html#k-means></href>  
(2): <href><http://scikit-learn.org/stable/modules/mixture.html></href>

***Question 7: Report the silhouette score for several cluster numbers you tried. Of these, which number of clusters has the best silhouette score?***

2: GMM: 0.415, KMeans: 0.426

3: GMM: 0.401, KMeans: 0.400

4: GMM: 0.314, KMeans: 0.335

My initial choice of model was the Gaussian Mixed Model and it looks like two clusters was optimal for this set. After comparing the KMeans with it however, we can notice that the KMeans score of 0.426 (still two clusters) performs slightly better than the GMM.

***Question 8: Consider the total purchase cost of each product category for the representative data points above, and reference the statistical description of the dataset at the beginning of this project. What set of establishments could each of the customer segments represent? Hint: A customer who is assigned to `'Cluster X'` should best identify with the establishments represented by the feature set of `'Segment X'`.***

<b>Segment 0</b> looks like a market of sorts. The very high spend on Fresh foods, mid spend on Milk, Grocery, and Frozen, and low spend in Detergents\_Paper and Delicatessen make it look like the focus is on fresh foods and other complimentary foods.<br>

<b>Segment1</b> might be a restaurant/cafe. We can see high spending in Milk, Grocery, and Detergents\_Paper. There is lower spending in the Fresh category.

***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?***

No, my predictions did not match these results. My initial thoughts were that point 0 would be close to the middle of the two clusters, but more on the restaurant/cafe side. The second point would also be restaurant/cafe. The third point I had predicted to be a market. All three points however, were classified as cluster 1, which I had guessed to be a restaurant/cafe.

***Question 10: Companies will often run*** [***[A/B tests]***]((https://en.wikipedia.org/wiki/A/B_testing)) ***when making small changes to their products or services to determine whether making that change will affect its customers positively or negatively. The wholesale distributor is considering changing its delivery service from currently 5 days a week to 3 days a week. However, the distributor will only make this change in delivery service for customers that react positively. How can the wholesale distributor use the customer segments to determine which customers, if any, would react positively to the change in delivery service? Hint: Can we assume the change affects all customers equally? How can we determine which group of customers it affects the most?***

The distributor can take each segment and split it them into two groups. In Segment0 there would be group A and group B and the same for Segment1. Each group should have an even spread of total spend. Our A group can be our constant group with no changes while the B group tries the new 3-day delivery program. If the program is successful in the B group, then it can be applied to the A group. Having the two segments helps us analyze what sorts of customers this affects and whether this would be applicable to all customers, just the ones in Segment0 or just the ones in Segment1.

***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 estimate for anticipated annual spending of each product category. Knowing these estimates, the wholesale distributor wants to classify each new customer to a customer segment to determine the most appropriate delivery service. How can the wholesale distributor label the new customers using only their estimated product spending and the customer segment data? Hint: A supervised learner could be used to train on the original customers. What would be the target variable?***

The wholesale distributor can label the new customers using the estimated spend and segment data by making a supervised learner that targets their segment. If we perform A/B testing for the current customers to help us discover what delivery methods work best for which segment, we would be able to find out how to allocate the most appropriate delivery methods for our new customers. For example, if we find that the best delivery method for Segment0 is 3 days, any customer, current or new, would use the 3-day delivery method. Customers who identify with Segment1 might have found that the original 5-day system worked best for them, so new and existing customers will continue doing that. We use feature we engineered through this project to engineer another that we could call “Delivery Method”.

***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?***

The two clusters that we predicted back in Question 7 are consistent with the customer segments here. The split and number of clusters we predicted are like the visualization. Our predictions of the cluster labels were flipped from the actual names though. Segment0 (the red cluster) we predicted to be a Farmer’s Market but it was Restaurants and Cafés while Segment1 (green grouping predicted as Restaurants and Cafés) was Retail. For this split, there are some points whom are much more defined than others. A handful of the Retail and Restaurant/Cafés points are mixed in the opposite clusters. There is no perfect way to split this data.