Homework 4

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Question 1: Clustering and PCA

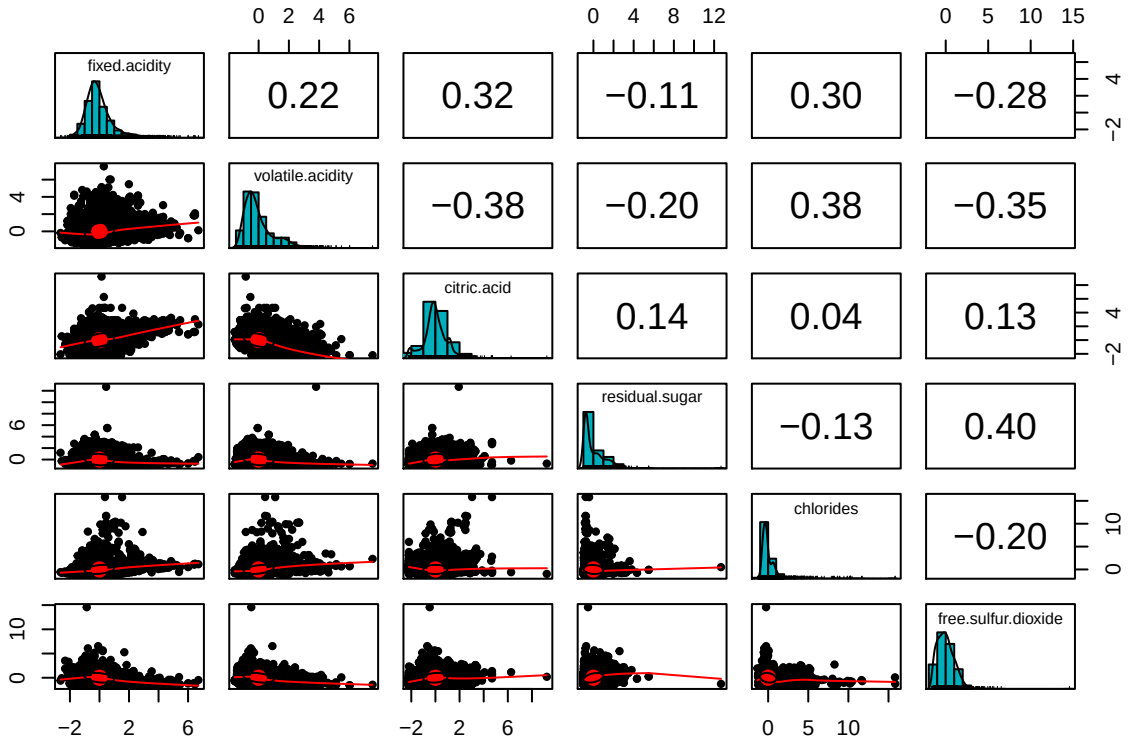
Given the fact that the **wines.csv** dataset consists of 11 chemical properties and 6,500 different bottles of *vinho verde* wine from northern Portugal, we have some difficulty determining which dimensionality reduction technique would be the better model for the task. With only 11 variables of the chemical properties of the wine, **Principal Component Analysis (PCA)** offers a easy-to-use tool to reduce the total number of variables down to a handful to work with, however at the same time, important information might be lost if the data is reduced to just a handful. On the other hand, **clustering** offers a method where all of the variables are at play, meaning that all 11 variables would be considered when determining which wine would be a part of which artificial group we are creating. However the drawback is that given the inherent randomization of cluster selection and our algorithm settings, we would have minute yet inconsistent results.

Principal Component Analysis

Our first dimensionality reduction technique would be Principal Component Analysis or PCA. In this case, the goal is to find low-dimensional summaries of high-dimensional data sets. As mentioned before, given the fact that our dataset only has 11 feature variables, the determination of what is high and low is a factor here. 11 variables by itself, is a rather low number of variables in play. However given its mathematical foundations, utilizing linear algebra to determine a vector subspace of the overall data, we capture the entirety of the data when determining our principal components.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	5.8184	0.0100	582.87	0.0000
scoresPC1	0.0382	0.0057	6.66	0.0000
scoresPC2	-0.1742	0.0063	-27.55	0.0000
scoresPC3	-0.1508	0.0080	-18.85	0.0000

With the results of our PCA regression, we find that with just three PCA components, we are able to find a model that has **residual standard error** 0.8046135 that captures a significant portion of the observations within the data. In addition, each coefficient's p-values indicate that each are well within the confidence level needed to utilize each principal component accurately.



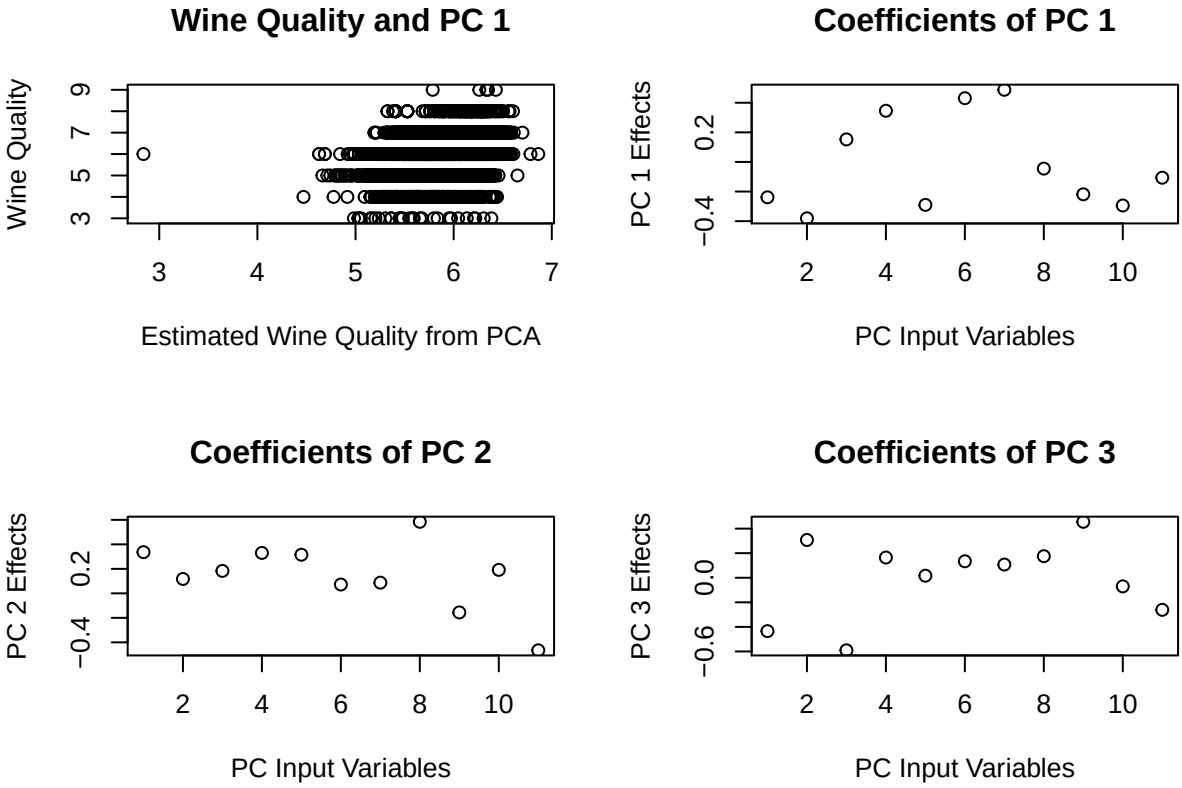
In this matrix of different plots, we take 6 from the 11 descriptor variables in the dataset and display the following:

- Bi-variate scatter plots below the diagonal
- Histograms on the diagonal
- Pearson correlation above the diagonal.

In the bi-variate scatter plots, we find a visual correlation between different variables. By utilizing PCA we can safely presume that linear combinations of similar variables would be a suitable approach in decomposing the data to a handful of variables.

While in the histograms on the diagonal, we see that once we normalize the underlying dataset, we would have a large concentration of values in the left hand side of the total range. Further supporting the notion that there is high correlation of similar wines.

Lastly, in the Pearson correlation, the rather low (relative to zero) values hints that there is little support for multicollinearity among the variables. Ultimately, PCA is one of two approaches we used to understand the data.



Before we move to our other approach, clustering, we present a 2x2 graph depicting the relationship of each PCA component among another. Given the scattered distribution of points, we find that there is considerable difficulty discerning the quality of wine based on the betas derived from each principal component.

Clustering

Our second method would be to apply a clustering algorithm on the data. Here we will apply a supervised learning algorithm to determine which wine type and quality level each of the wines in our dataset would be. Given our rather small categorical classifications: **red** or **white** this approach would be accurate enough to correctly classify the majority of the wines in question. Given our linear scale, be able to predict the wine quality within a close parameter of the underlying wine judged quality level. With only two clusters to predict, we have an easier time implementing the code to achieve better results.

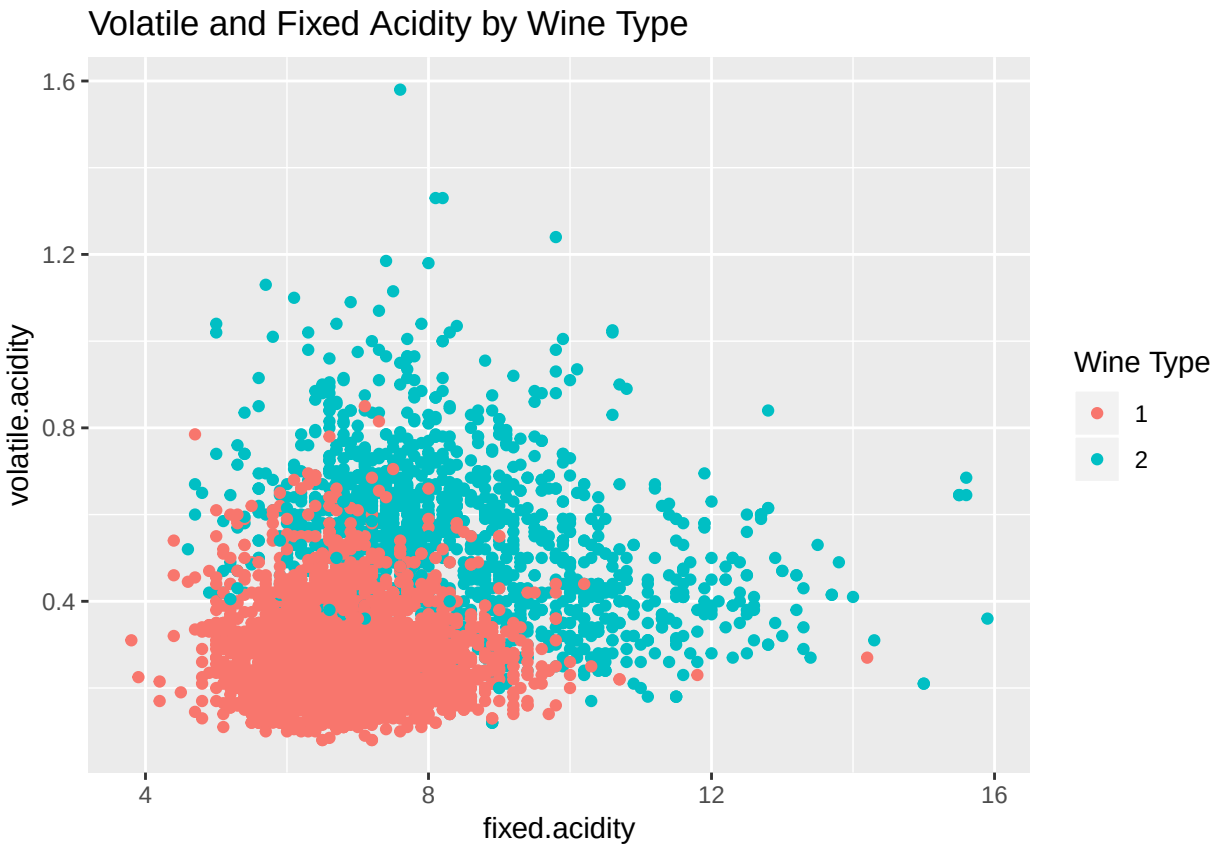
```
## [1] "Cluster 1"
```

```
##        fixed.acidity     volatile.acidity          citric.acid
##           6.85066928           0.27395181           0.33576400
##       residual.sugar            chlorides  free.sulfur.dioxide
##           6.40047364           0.04519007          35.62149918
## total.sulfur.dioxide              density                   pH
##         138.66422982           0.99401827           3.18893740
```

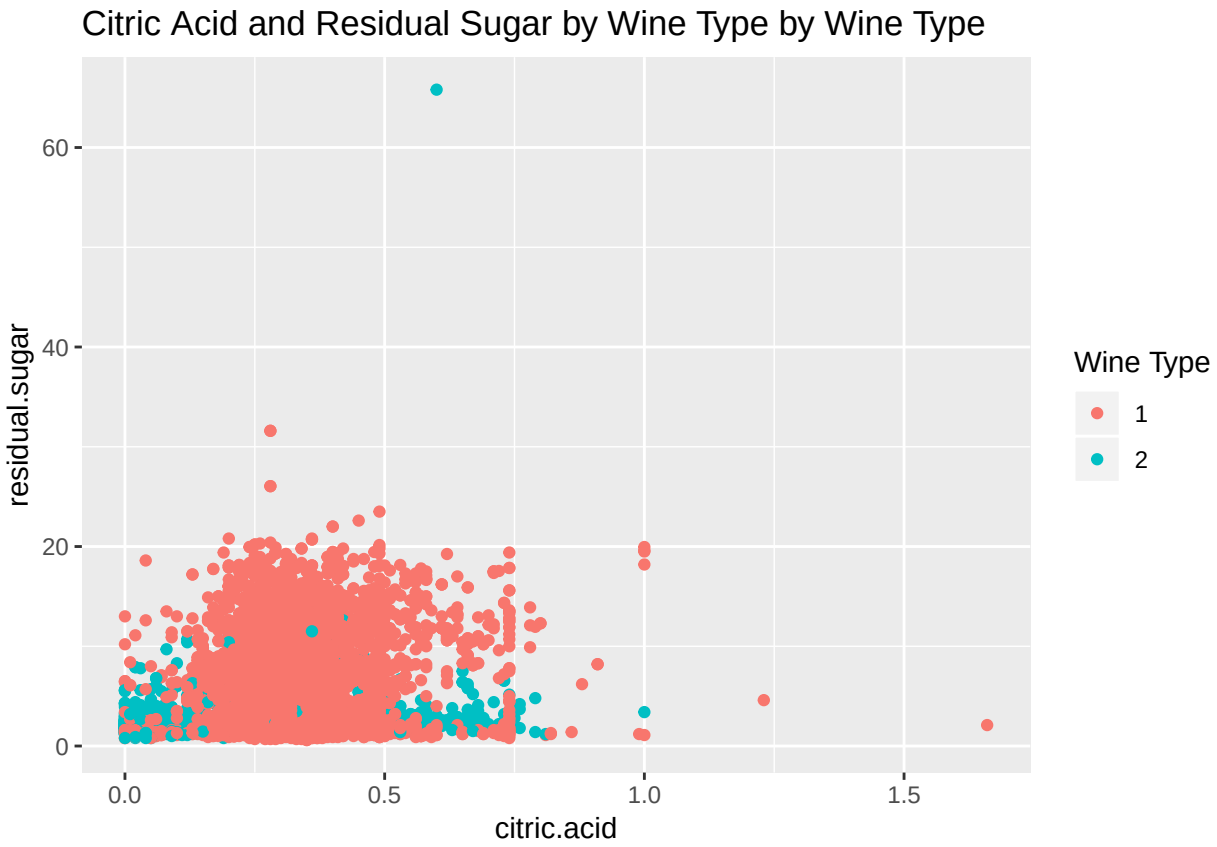
```
## [1] "Cluster 2"
```

```
##        fixed.acidity     volatile.acidity          citric.acid
##           8.29433272           0.53412553           0.26794028
##       residual.sugar            chlorides  free.sulfur.dioxide
##           2.61060329           0.08812249          15.44485070
## total.sulfur.dioxide              density                   pH
##          47.92138940           0.99670402           3.30598416
```

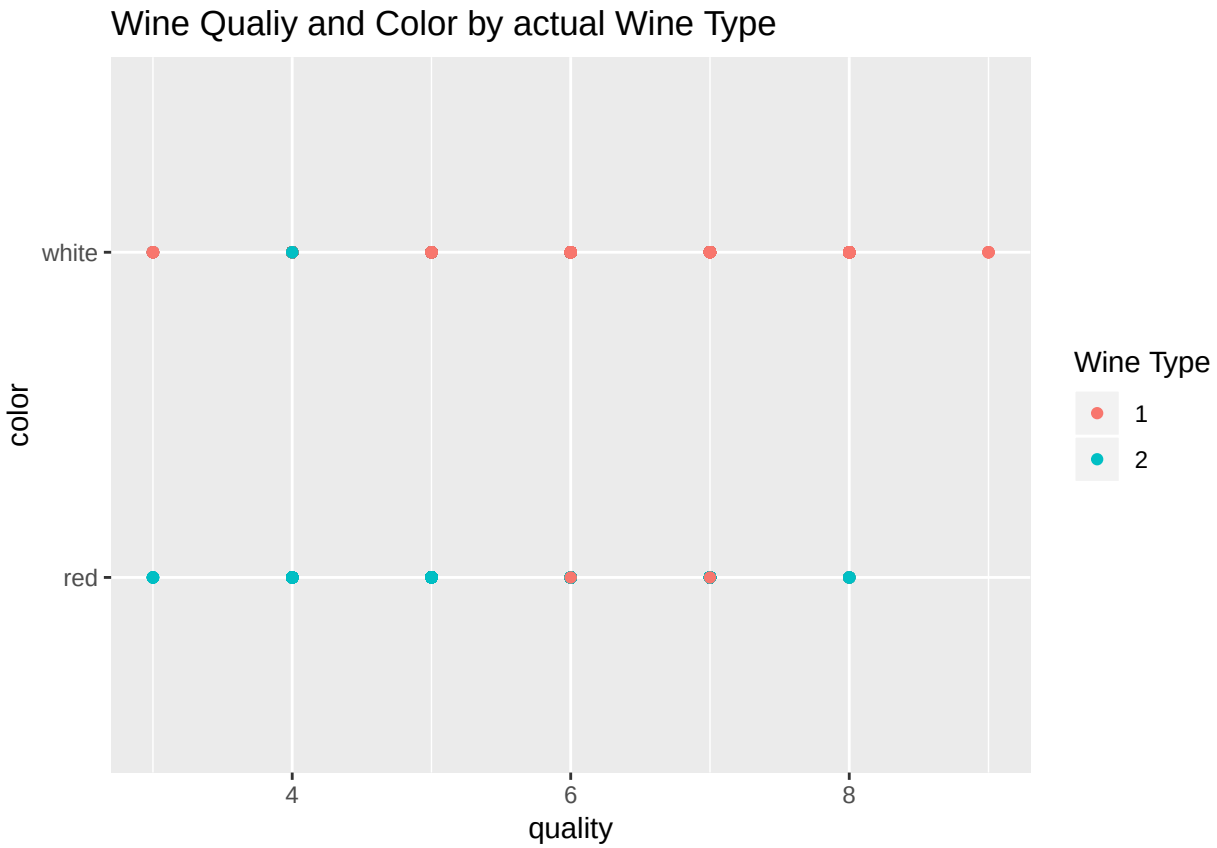
Here we have the criteria that the algorithm devised to determine which wine would be assigned to which cluster category. We see that given two clusters to work with, either one presumably to determine whether or not it is white or red wine, we can see distinct differences in all of the cutoff levels for each variable.



By comparing our two variable relating to acidity **Volatile Acidity** and **Fixed Acidity** we find that the clustering algorithm has captured the two main groups of wine with an intermixed amount near the middle diagonal. As we depict more comparisons, we will find that the cluster approach produces an easier to understand graph of the results.



Here is an example where clustering failed to adequately determine the correct wine type based on the **Residual Sugar** and **Citric Acid** samples of the wine. With **Red** as *1* and **White** wines tagged as *2*, we find that the clustering method incorrectly created a large centroid of wines near the center of the mass.

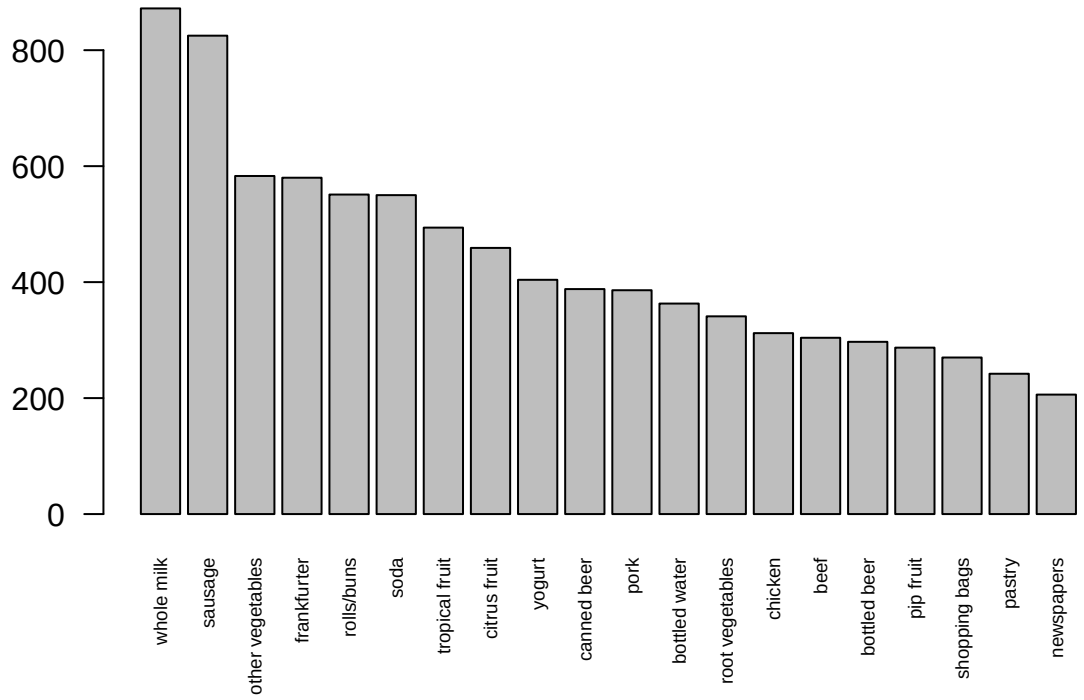


Lastly we have the final clustering of the wine **Color** and **Quality**. The clustering approach correctly labels all but one of the white wines while missing all but two of the reds. Given the fact that there are only colors of wines to work with, missing even one or two of the wine set would mean that although a cluster approach would be easier to implement, it will still miss 10% or more of the time when determining whether or not a wine is red or white.

Question 2: Market Segmentation

Question 3: Association Rules for Grocery Purchases

The problem of any grocery marketer is what items to stock and in what quantities. If there are certain groups of products, like peanut butter and jelly with bread, then it would make sense to stock items of group value. Market basket analysis has the purpose of quantifying items within the shelves in a store. Placing products is more of an art than a science - however it doesn't mean data analysis should not be a major component in its creation. The goal is to influence customer purchasing habits to chain-buy their groceries. With this in mind, we will delve into the data set at hand.



Here is a list of the top items within the data set. It is clear that the most popular item is milk. Being the mainstay of various food groups, milk and cereal, milk and baking, milk in .

With only 2160 rules created, this is a good start in understanding the associations of different goods within the data set. But the holy grail is to visualize the data using a network graph.

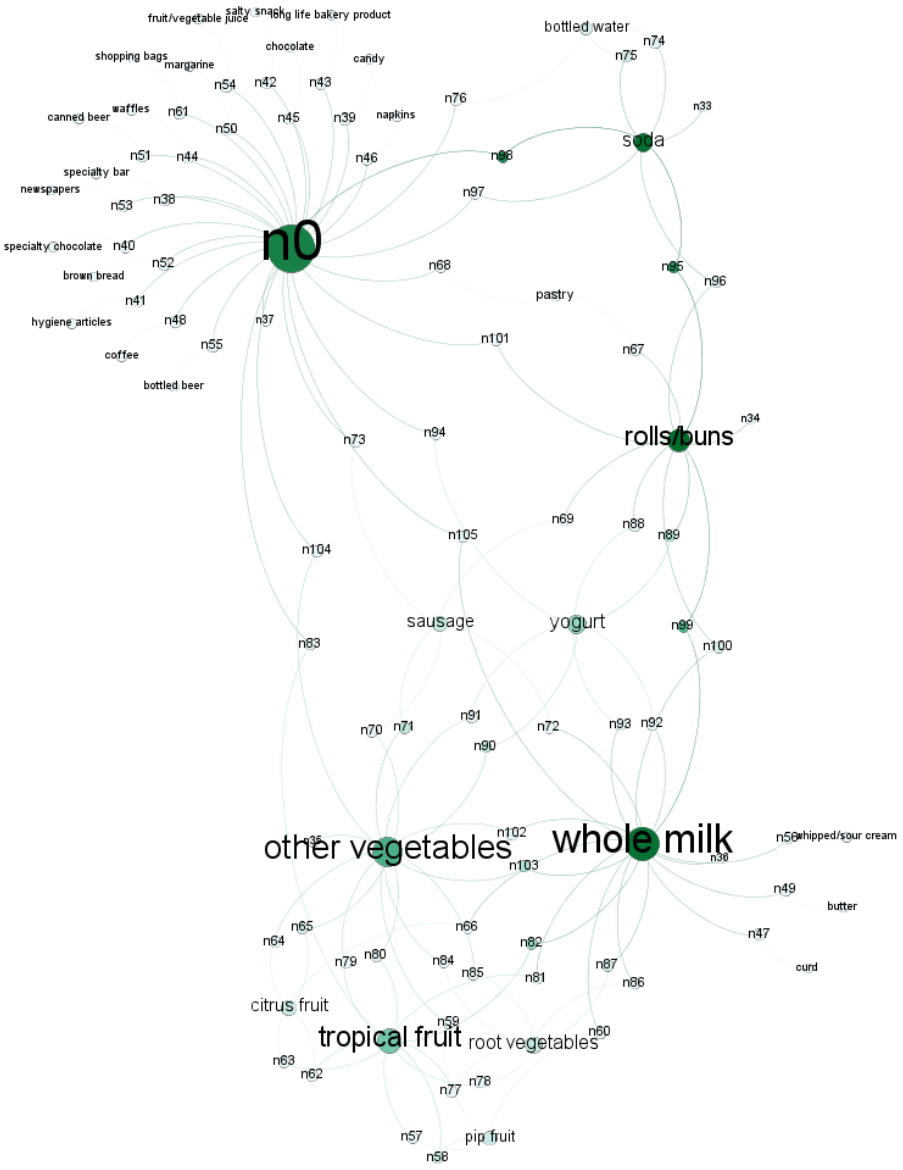


Figure 1: Market Basket Association Network