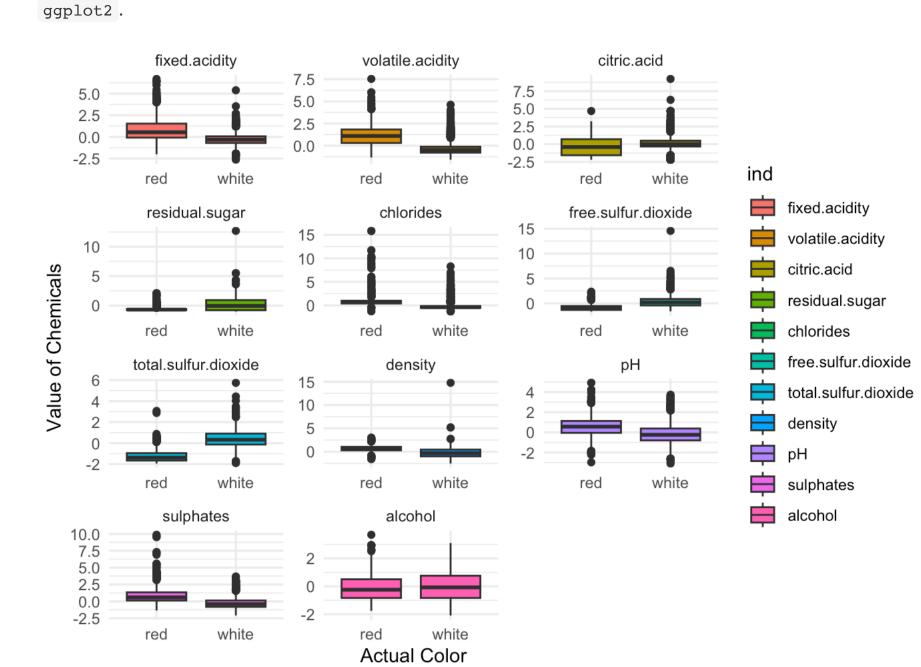
2024-04-21

Question 1: Clustering and PCA

Clustering

Color of wines

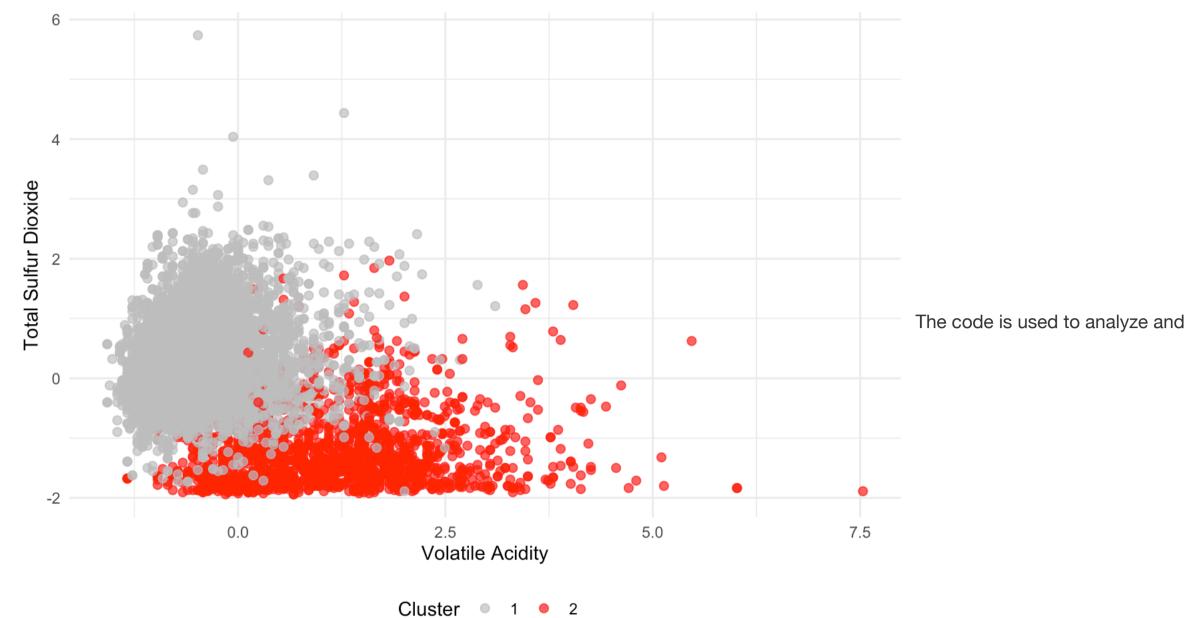
We standardizes the features of a wine dataset, excluding quality and color, and performs K-means clustering with two different numbers of centers (2 and 7). Then we visualizes the distribution of various chemical properties across actual wine colors using a box plot created with



From the above results, it can be concluded that "colors can be most distinctly differentiated by volatile acidity and total sulfur dioxide." In the box plots, it is observed that these two chemical substances show significant differences in median values among different colors of wine.

volatile.acidity and total.sulfur.dioxide

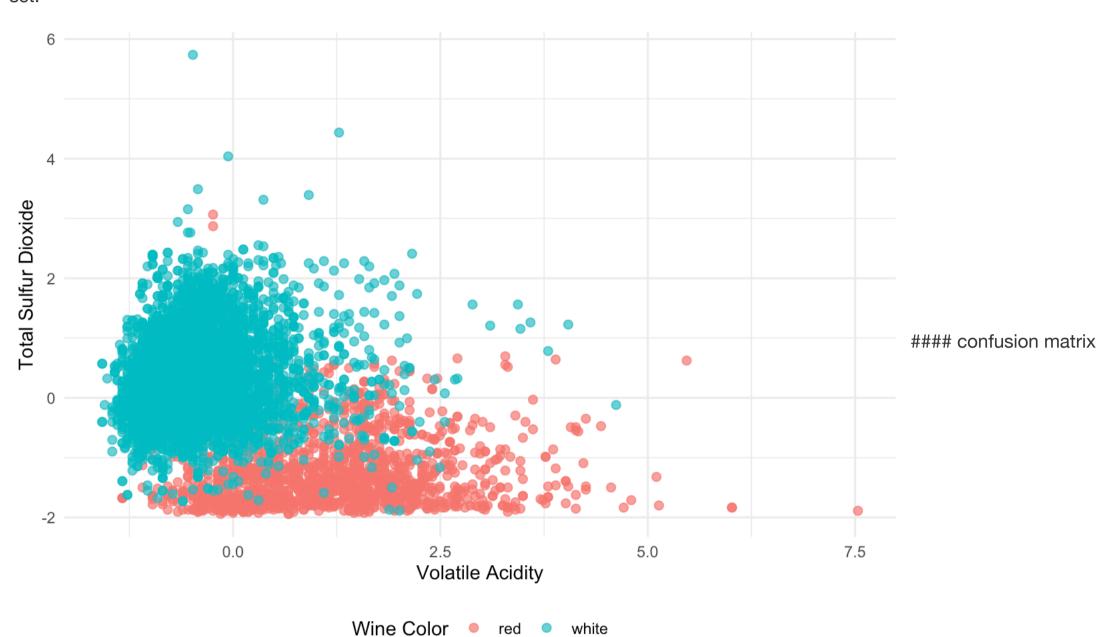
We attempt to show in the scatter plot how two chemical components of wine data are clustered according to color, marked by different colors for different cluster groups (volatile acidity, total sulfur dioxide). This visually demonstrates how these chemical components are distributed across different clusters.



been identified as white wine, while the second group has been identified as red wine.

The code below show the distribution of existing wine color classifications and chemical properties (volatile acidity and total sulfide) in the data set.

visualize how well the clustering algorithm classifies wines based on their chemical properties. Through clustering analysis, the first group has



Predicted

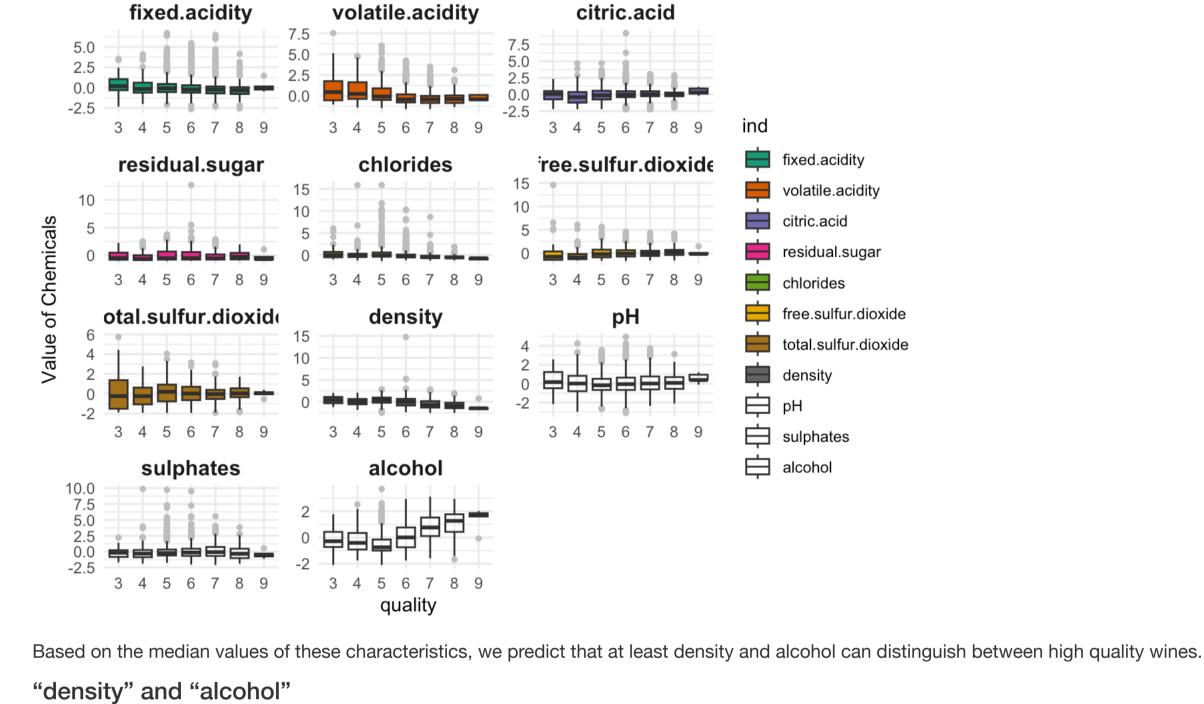
Using the confusion matrix to evaluate K-means can verify how the clusters align with the actual labels, especially in scenarios where color

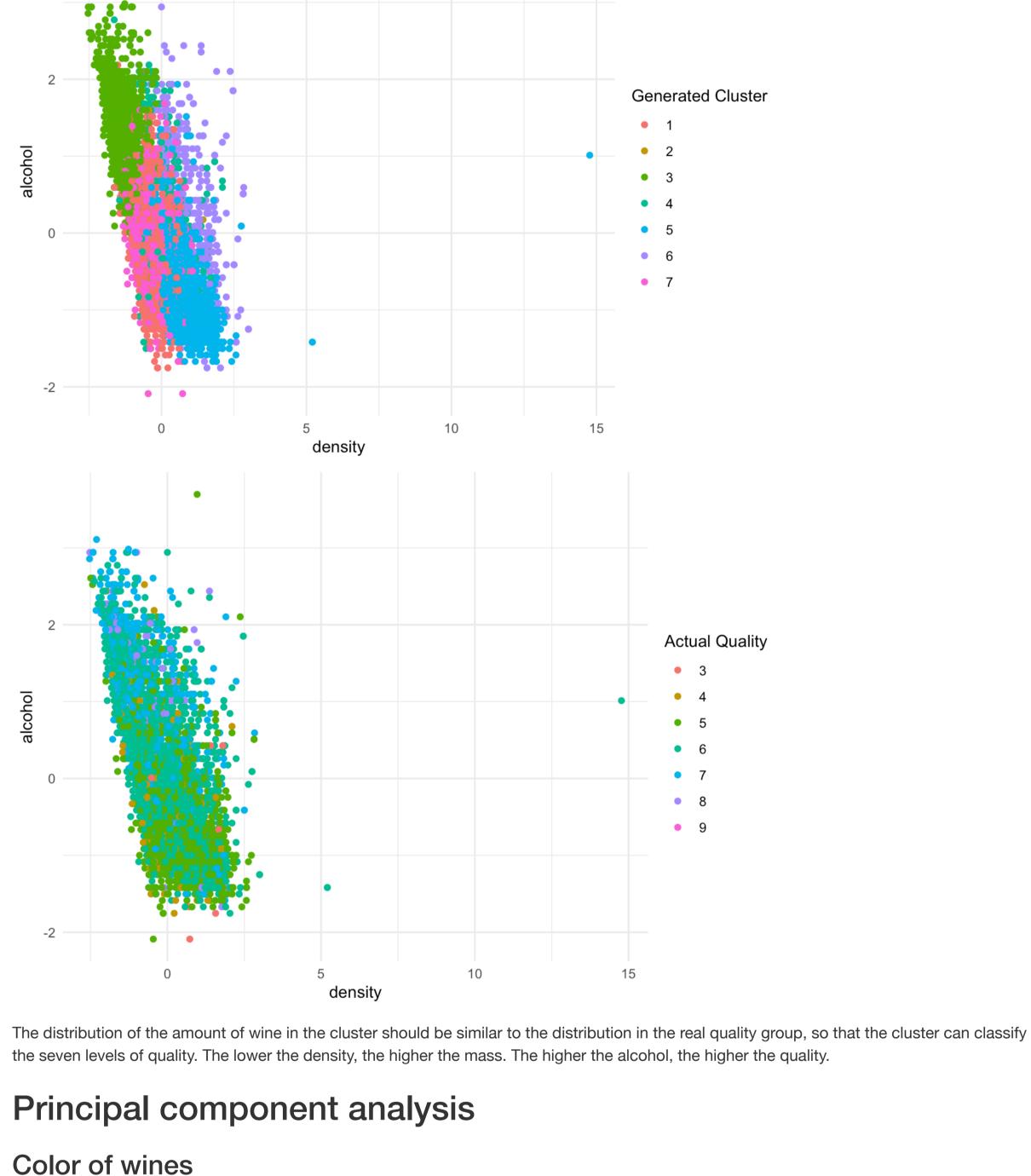
```
## Actual
                       68
                 24 1575
       red
The clustering accuracy of category 1 (white wine) is very high because the vast majority of white wines are correctly grouped into this category.
```

Category 2 (red wine) also showed high clustering accuracy, with most red wines correctly identified. The relatively small number of misclassifications suggests that the K-means clustering algorithm's ability to distinguish between red and white wines on this dataset is fairly accurate. **Quality of wines**

clusters are clustered, such as red wine versus white wine.

This code is used to create a boxplot to visualize the distribution of chemical composition values for wines of different qualities, thereby helping the observer understand the chemical differences between wine qualities.





load matrix of PCA We try to generate the load matrix of PCA

PC4

0.2127849

PC1 PC2 PC3 0.1643462 -0.1474804 -0.2045537 -0.2830794 fixed.acidity

volatile.acidity -0.3807575 -0.1175497 0.3072594 citric.acid 0.1523884 -0.1832994 -0.5905697 -0.2643003 -0.1553487 0.2276338 -0.3812850 -0.2934123 0.4026887 -0.2344633 -0.0011090

residual.sugar 0.3459199 -0.3299142 0.1646884 chlorides

chlorides	-0.2901126	-0.315258	30 0.01	66791	-0.244743	9 0.6143	3911 0.1	609764	-0.0460682	-0.4715168	-0.2964437	0.1966302	0.0434376
free.sulfur.dioxide	0.4309140	-0.071932	26 0.13	42239	-0.357278	9 0.2235	5323 -0.3	400514	-0.2993632	0.2078076	-0.3666563	-0.4802433	-0.0002125
This load matrix tell us how much each variable contributes to the construction of each principal component. It can explain what aspects of the data each principal component represents. In general, the greater the absolute value of the weight, the greater the influence of the variable on the corresponding principal component. Statistical overview of the importance of principal components in PCA results													
## Importance	of componen	ts:											
##		PC1	PC2	PC3	PC4	PC5	PC6	PC	:7				
## Standard de	viation	1.7407	1.5792	1.2475	0.98517	0.84845	0.77930	0.7233	0				
## Proportion	of Variance	0.2754	0.2267	0.1415	0.08823	0.06544	0.05521	0.0475	6				

0.1674430 -0.3533619 -0.2334778

PC5

0.1514560 -0.4921431

PC6

PC7

-0.3891598

PC8

-0.0874351

0.2179755 -0.5248729 -0.1080032

0.4012356 -0.3440567

PC9

0.4969327

PC10

-0.1521767

PC11

0.0847718

From this output, we typically focus on those points where the cumulative variance ratio approaches 1 to determine how many principal components need to be retained. In many cases, it is only when the cumulative variance ratio reaches a high value (such as 80% or 90%) that we believe we have captured most of the information in the data set. In this example, the first seven principal components already explain more than 90% of the variance in the data, so all 11 principal components may not be needed to capture most of the information in the data set.

The first two components, which have the biggest variance, seem to distinguish the color of the wine well; Principal component analysis (PCA) results in the first and second principal components

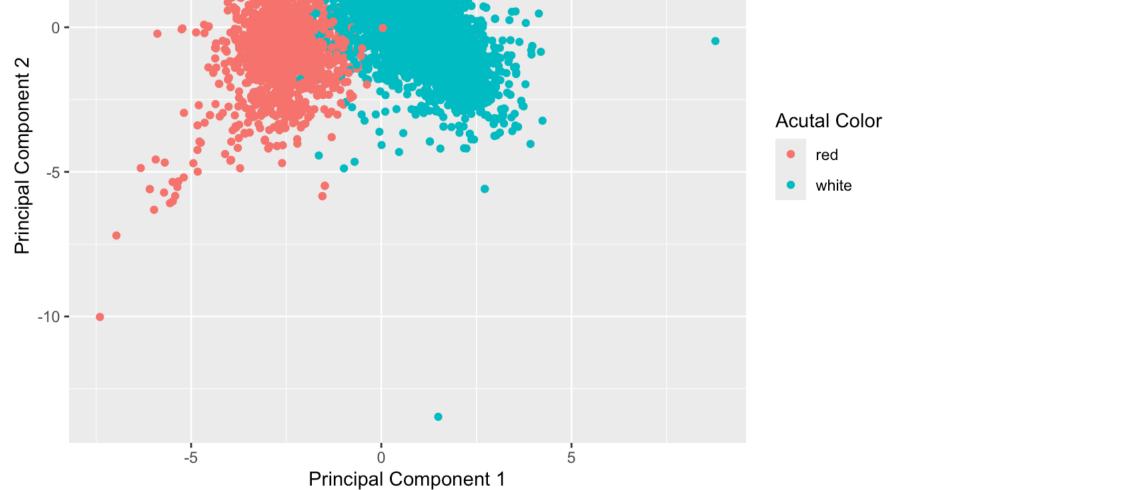
The first two components, which have the biggest variance, seem to distinguish the color of the wine well.

Cumulative Proportion 0.2754 0.5021 0.6436 0.73187 0.79732 0.85253 0.90009

PC9 PC10 PC11

PC8

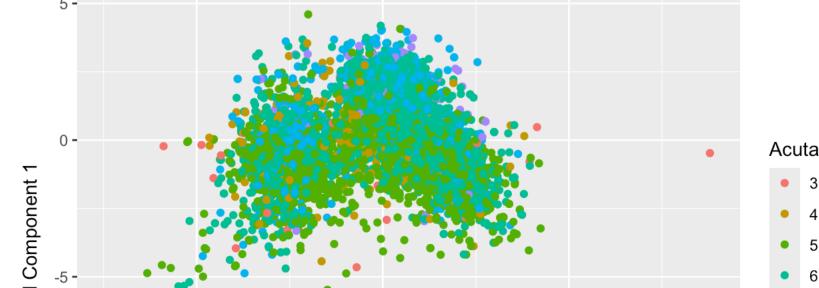
Standard deviation 0.70817 0.58054 0.4772 0.18119 ## Proportion of Variance 0.04559 0.03064 0.0207 0.00298 ## Cumulative Proportion 0.94568 0.97632 0.9970 1.00000



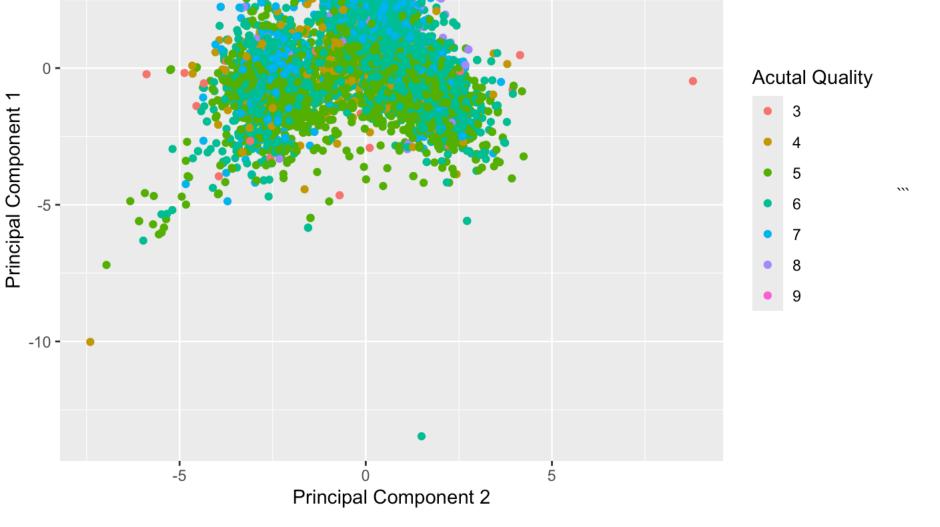
We confirmed that red and white wines can be distinguished using principal component 1 (PC1): white wines tend to have higher PC1 scores

than red wines. **Quality of wines**

PCA of Quality of Wine



Exploring the relationship between wine quality and principal components



When different colors are used to signify the quality of wines, the clusters overlap significantly, rendering the PCA output inconclusive. It appears that PCA does not effectively differentiate between wines of higher and lower quality.

conclusion

To sum up, while PCA and clustering algorithms can differentiate red from white wines, it appears that neither method is effective at discerning wines of higher quality from those of lower quality. However, in k-means algorithm, two characteristics of density and alcohol content can be used to identify high-quality wine to a certain extent.