Project Proposal

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```
library("cowplot")
## Loading required package: ggplot2
##
## Attaching package: 'cowplot'
## The following object is masked from 'package:ggplot2':
##
##
       ggsave
library("tibble")
library("dplyr")
##
## Attaching package: 'dplyr'
##
  The following objects are masked from 'package:stats':
##
##
       filter, lag
## The following objects are masked from 'package:base':
##
##
       intersect, setdiff, setequal, union
library("ggplot2")
library("broom")
library("knitr")
```

Introduction

Project Goal: Explanation

To identify variables that are important in explaining variation in the response.

We are interested in researching what factors contribute to the quality of wine for different types of red vinho verde from Portugal. This data set was used to predict quality of wine for future wine certification, complementary to human wine tasters, in the paper we cited (*Modeling wine preferences by data mining from physicochemical properties*). We believe that this dataset can also be used to analyze what chemical factors are attributable to the final rating of wine (measured by the variable quality). If we can understand how chemical factors affect the wine quality, it may shed light on future R&D directions for chemical methods that could improve/preserve wine quality.

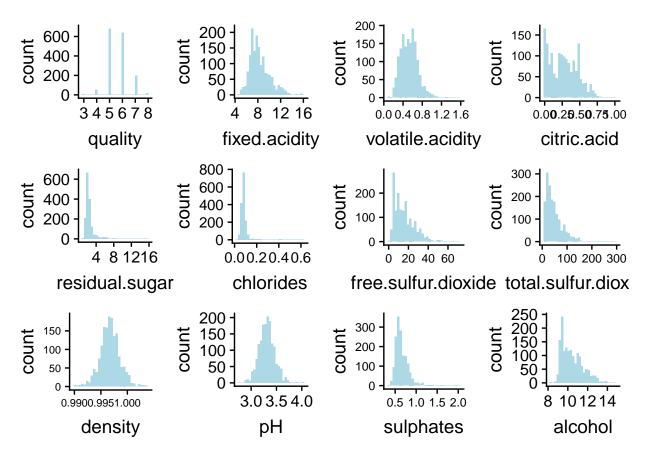
In the beginning stage of the modeling process, we will **try to include all variables** that might be related to the response variable (quality), even if they are not statistically significant. By doing so, we can maximize the fitness of this model. We would also like to **mean-center** all numerical explanatory variables to obtain more meaningful interpretation of each chemical factor by its statistical coefficient. At the end, we will produce a regression model that best explains how different chemical compositions of the wine (red vinho verde) determines the variation in wine quality.

Data

```
# input data source
data <- read.csv("./redwine_quality.csv")</pre>
# overview of the dataset
glimpse(data)
## Observations: 1,599
## Variables: 12
                          <dbl> 7.4, 7.8, 7.8, 11.2, 7.4, 7.4, 7.9, 7.3, ...
## $ fixed.acidity
## $ volatile.acidity
                          <dbl> 0.700, 0.880, 0.760, 0.280, 0.700, 0.660,...
                          <dbl> 0.00, 0.00, 0.04, 0.56, 0.00, 0.00, 0.06,...
## $ citric.acid
## $ residual.sugar
                          <dbl> 1.9, 2.6, 2.3, 1.9, 1.9, 1.8, 1.6, 1.2, 2...
## $ chlorides
                          <dbl> 0.076, 0.098, 0.092, 0.075, 0.076, 0.075,...
## $ free.sulfur.dioxide <dbl> 11, 25, 15, 17, 11, 13, 15, 15, 9, 17, 15...
## $ total.sulfur.dioxide <dbl> 34, 67, 54, 60, 34, 40, 59, 21, 18, 102, ...
## $ density
                          <dbl> 0.9978, 0.9968, 0.9970, 0.9980, 0.9978, 0...
## $ pH
                          <dbl> 3.51, 3.20, 3.26, 3.16, 3.51, 3.51, 3.30,...
## $ sulphates
                          <dbl> 0.56, 0.68, 0.65, 0.58, 0.56, 0.56, 0.46,...
## $ alcohol
                          <dbl> 9.4, 9.8, 9.8, 9.8, 9.4, 9.4, 9.4, 10.0, ...
## $ quality
                          <int> 5, 5, 5, 6, 5, 5, 5, 7, 7, 5, 5, 5, 5, 5, ...
There are 1,599 observations and 12 variables in this dataset.
# summary statistics of each variable
summary(data)
## fixed.acidity
                    volatile.acidity citric.acid
                                                     residual.sugar
## Min. : 4.60
                   Min.
                           :0.1200
                                    Min.
                                            :0.000
                                                     Min. : 0.900
## 1st Qu.: 7.10
                    1st Qu.:0.3900
                                     1st Qu.:0.090
                                                     1st Qu.: 1.900
                                                     Median : 2.200
## Median : 7.90
                   Median :0.5200
                                     Median :0.260
## Mean
          : 8.32
                    Mean
                           :0.5278
                                     Mean
                                            :0.271
                                                     Mean
                                                           : 2.539
##
  3rd Qu.: 9.20
                    3rd Qu.:0.6400
                                     3rd Qu.:0.420
                                                     3rd Qu.: 2.600
##
  Max.
           :15.90
                    Max.
                           :1.5800
                                     Max.
                                            :1.000
                                                     Max.
                                                            :15.500
##
      chlorides
                      free.sulfur.dioxide total.sulfur.dioxide
                      Min. : 1.00
##
           :0.01200
                                          Min.
                                                 : 6.00
  Min.
  1st Qu.:0.07000
                     1st Qu.: 7.00
                                          1st Qu.: 22.00
  Median :0.07900
                                          Median : 38.00
##
                      Median :14.00
## Mean
           :0.08747
                      Mean
                            :15.87
                                          Mean
                                                : 46.47
##
   3rd Qu.:0.09000
                      3rd Qu.:21.00
                                          3rd Qu.: 62.00
##
   Max.
           :0.61100
                      Max.
                             :72.00
                                          Max.
                                                 :289.00
##
                                       sulphates
      density
                           Щq
                                                         alcohol
##
   Min.
           :0.9901
                           :2.740
                                     Min.
                                            :0.3300
                                                      Min.
                                                             : 8.40
                     Min.
##
   1st Qu.:0.9956
                     1st Qu.:3.210
                                     1st Qu.:0.5500
                                                      1st Qu.: 9.50
## Median :0.9968
                     Median :3.310
                                     Median :0.6200
                                                      Median :10.20
## Mean
         :0.9967
                     Mean
                           :3.311
                                     Mean
                                           :0.6581
                                                      Mean
                                                            :10.42
   3rd Qu.:0.9978
                     3rd Qu.:3.400
                                     3rd Qu.:0.7300
##
                                                      3rd Qu.:11.10
##
  Max.
          :1.0037
                     Max. :4.010
                                     Max. :2.0000
                                                      Max.
                                                             :14.90
##
      quality
##
   Min.
           :3.000
##
  1st Qu.:5.000
## Median :6.000
## Mean
          :5.636
## 3rd Qu.:6.000
```

```
## Max.
           :8.000
p1 <- ggplot(data = data, aes(x = quality)) + geom_histogram(fill= "lightblue")
p2 <- ggplot(data = data, aes(x = fixed.acidity) ) + geom_histogram(fill= "lightblue")
p3 <- ggplot(data = data, aes(x = volatile.acidity)) + theme(axis.text=element_text(size=9)) + geom_h
p4 <- ggplot(data = data, aes(x = citric.acid)) + theme(axis.text=element_text(size=9)) + geom_histog
p5 <- ggplot(data = data, aes(x = residual.sugar)) + geom_histogram(fill= "lightblue")
p6 <- ggplot(data = data, aes(x = chlorides) ) + theme(axis.text=element_text(size=11)) + geom_histogr
p7 <- ggplot(data = data, aes(x = free.sulfur.dioxide)) + theme(axis.text=element_text(size=9)) + geo
p8 <- ggplot(data = data, aes(x = total.sulfur.dioxide)) + theme(axis.text=element_text(size=9)) + ge
p9 <- ggplot(data = data, aes(x = density)) + theme(axis.text=element_text(size=7.5)) + geom_histogram
p10 <- ggplot(data = data, aes(x = pH)) + geom_histogram(fill= "lightblue")
p11 <- ggplot(data = data, aes(x = sulphates) ) + theme(axis.text=element_text(size=9)) + geom_histogram
p12 <- ggplot(data = data, aes(x = alcohol)) + geom_histogram(fill= "lightblue")
plot_grid(p1,p2,p3,p4,p5,p6,p7,p8,p9,p10,p11,p12,ncol = 4,nrow = 3)
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
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`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.



Most of the 12 variables are pretty normally distributed. But variables like free.sulfur.dioxide, total.sulfur.dioxide, and alcohol are slightly skewed to the right.

Variable Description

Response Variable:

• quality: the quality of the wine (a score between 0 and 10)

Explanatory Variables:

- fixed.acidity: $(g(tartaric\ acid)/dm^3)$ the amount of acid in wine that's not volatile (do not evaporate fast)
- volatile.acidity: $(g(acetic\ acid)/dm^3)$ the amount of acetic acid in wine; at high levels can lead to an unpleasant and vinegar taste in wines
- citric.acid: (g/dm^3) citric acid is found in small quantities, and can add freshness and flavor to wines
- residual.sugar: (g/dm^3) the amount of sugar left after fermatation stops; generally greater than 1 gram/liter in wines and wines with greater than 45 grams/liter are considered sweet
- chlorides: $(g(sodium\ chloride)/dm^3)$ the amount of salt in the wine
- free.sulfure.dioxide: (mg/dm^3) the free form of $S0_2$ exists in equilibrium between molecular $S0_2$ (as a dissolved gas) and bisulfite ion
- total.sulfur.dioxide: (mg/dm^3) amount of free and bound forms of $S0_2$; at free $S0_2$ concentration over 50ppm, $S0_2$ becomes evident in the smell and taste of the wine

- density: (g/cm^3) the density of the liquid, which is close to the density of water depending on the percent alcohol and sugar content in the wine
- **pH:** the indicator of the acidicity or basic property of the wine on a scale from 0 (very acidic) to 14 (very basic)
- sulphates: $(g(potassium\ sulphate)/dm^3)$ a wine additive which can contribute to sulfur dioxide gas $S0_2$ levels
- alcohol: (vol.%) the percent alcohol content of the wine.

Analysis

In our data set, the response variable quality is an ordinal data with a scale of 0 to 10. **Quality** is currently an integer variable in the dataset, but for modeling purposes, we might convert it into factor variable type. We will investigate 11 explanatory variables to understand their main effect and interaction effect on the wine quality (response variable).

Our **main objective** of the study is to understand which explanatory variables play a significant influence on the quality of the wine.

Our current hypothesis is that:

Proposed methods:

Data Exploration

- Plot the relationships of each explanatory variable vs. the response variable quality and all other
 explanatory variables so that we can have a rough idea of variables' relationships, identify outliers, and
 needs for data transformation.
- Based on the findings from the plots, we will focus on strong linear/non-linear relationships/significant
 multicollinearity detected. Through inspection of variable definitions, we believe free sulphur dioxide
 could be directly related to total sulphur dioxide, which is one potential multicollinearity we will test
 on. A comprehensive test of strong correlation/multicollinearity will be conducted on other explanatory
 variables as well.
- Analyze the distribution of each variables, specifically histogram and summary statistics of mean, median, and standard deviation for numerical data types, to further inspect for missing value, outliers, and potential data transformation.
- Given our response variable (quality) is a categorical variable, we might transform it from an integer type to a factor variable. We can then create a bar graph and calculate the number of observations in each quality rating using the group_by() and summarise() functions. This analysis of the distribution of quality can then help us determine the most appropriate reference level.

Regression Analysis

- Conduct linear regression models using explanatory variables and the response variable after adjusting for any findings in the Data Exploration stage (e.g. add a new variable for data transformation).
- We will use a stepwise model selection to choose variables for the model, including only main effects.
- We might also conduct model selection using forward and backward procedure, depending on the explanatory variables included in the previous model selection, and compare their differences
- After deciding on the model, we will conduct Nested F tests to determine any significant interaction
 effects among the explanatory variables. For example, density, residual sugar, density, alcohol, according
 to variable definitions.
- Create a final model based on previous results.
- Check for model fit (i.e. R2value)

Assumptions

- Check if the final linear regression model meets the assumptions for regression: linearity, constant variance, independence and normality using standardized residual plots, histogram (distribution of residuals), and QQ-plot.
- Try to improve the model if certain assumptions are not met.
- Check for potential influence points and see how they might affect the model fit. We will test for leverage and Cook's Distance and draw conclusions along with the standardized residual plots.
- Calculate multicollinearity using the vif() function.

Conclusion

• After finalizing our model and making sure it meets all assumptions, we will draw the final conclusion on our research interest, and identify factors influencing the wine quality.

Reference

https://www.kaggle.com/uciml/red-wine-quality-cortez-et-al-2009

 $https://ac.els-cdn.com/S0167923609001377/1-s2.0-S0167923609001377-main.pdf?_tid=949194e4-fb5f-4ecc-8572-25fb69b53955acdnat=1541795552_dd074c301f5165bdbe4ba634ffcd1534$

Appendix