

Data 621 - Homework 5

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Overview:

We will explore, analyze and model a data set containing information on approximately 12,000 commercially available wines. The variables are mostly related to the chemical properties of the wine being sold. The response variable is the number of sample cases of wine that were purchased by wine distribution companies after sampling a wine. These cases would be used to provide tasting samples to restaurants and wine stores around the United States. The more sample cases purchased, the more likely is a wine to be sold at a high end restaurant. A larger wine manufacturer is studying the data in order to predict the number of wine cases ordered based upon the wine characteristics. If the wine manufacturer can predict the number of cases, then that manufacturer will be able to adjust their wine offering to maximize sales.

Objective

Build a count regression model to predict the number of cases of wine that will be sold given certain properties of the wine. HINT: Sometimes, the fact that a variable is missing is actually predictive of the target.

Description

Below is a short description of the variables of interest in the data set:

VARIABLE NAME:	DEFINITION:	THEORETICAL EFFECT:
INDEX	Identification Variable (do not use)	None
TARGET	Number of Cases Purchased	None
AcidIndex	Proprietary method of testing totalacidity of wine by using a weighted average	
Alcohol	Alcohol Content	
Chorides	Cholride content of wine	
CitricAcid	Citric Acid Content	
Density	Density of Wine	
FixedAcidity	Fixed Acidity of Wiine	
FreeSulfurDioxide	Sulfur Dioxide content of wine	
LabelAppeal	Marketing Score indicating the appeal of label design for consumers. High numbers suggest customers like the label design. Negative numbers suggest customers don't like the design.	Many consumers purchase based on the visual appeal of the wine label design. Higher numbers suggest better sales.
ResidualSugar	Residual Sugar of wine	
STARS	Wine rating by a team of experts: 4 Stars = Excellent, 1 Star = Poor	A high number of stars suggests high sales
Sulphates	Sulfate content of Wine	
TotalSulfurDioxide	Total Sulfur Dioxide of Wine	
VolatileAcidity	Volatile Acid content of wine	
pH	pH of wine	

Load Libraries:

These are the libraries used to explore, prepare, analyze and build our models

```
library(tidyverse)
library(dplyr)
library(corrplot)
library(skimr)
library(DataExplorer)
library(ggplot2)
library(hrbrthemes)
library(mice)
library(MASS)
library(dvmisc)
library(gridExtra)
library(lattice)
```

Load Data set:

We have included the original data sets in our GitHub account and read from this location. Below we are showing the training data set:

```
## INDEX TARGET FixedAcidity VolatileAcidity CitricAcid ResidualSugar Chlorides
## 1 1 3 3.2 1.160 -0.98 54.2 -0.567
## 2 2 3 4.5 0.160 -0.81 26.1 -0.425
## 3 4 5 7.1 2.640 -0.88 14.8 0.037
## 4 5 3 5.7 0.385 0.04 18.8 -0.425
## 5 6 4 8.0 0.330 -1.26 9.4 NA
## 6 7 0 11.3 0.320 0.59 2.2 0.556
## FreeSulfurDioxide TotalSulfurDioxide Density pH Sulphates Alcohol
## 1 NA 268 0.99280 3.33 -0.59 9.9
## 2 15 -327 1.02792 3.38 0.70 NA
## 3 214 142 0.99518 3.12 0.48 22.0
## 4 22 115 0.99640 2.24 1.83 6.2
## 5 -167 108 0.99457 3.12 1.77 13.7
## 6 -37 15 0.99940 3.20 1.29 15.4
## LabelAppeal AcidIndex STARS
## 1 0 8 2
## 2 -1 7 3
## 3 -1 8 3
## 4 -1 6 1
## 5 0 9 2
## 6 0 11 NA
```

Data Exploration:

Using the `summary()` function lets start exploring the training and evaluation data.

Training:

```
## INDEX TARGET FixedAcidity VolatileAcidity
## Min. : 1 Min. :0.000 Min. : -18.100 Min. : -2.7900
## 1st Qu.: 4038 1st Qu.:2.000 1st Qu.: 5.200 1st Qu.: 0.1300
## Median : 8110 Median :3.000 Median : 6.900 Median : 0.2800
## Mean : 8070 Mean :3.029 Mean : 7.076 Mean : 0.3241
## 3rd Qu.:12106 3rd Qu.:4.000 3rd Qu.: 9.500 3rd Qu.: 0.6400
## Max. :16129 Max. :8.000 Max. : 34.400 Max. : 3.6800
##
## CitricAcid ResidualSugar Chlorides FreeSulfurDioxide
## Min. : -3.2400 Min. : -127.800 Min. : -1.1710 Min. : -555.00
## 1st Qu.: 0.0300 1st Qu.: -2.000 1st Qu.: -0.0310 1st Qu.: 0.00
## Median : 0.3100 Median : 3.900 Median : 0.0460 Median : 30.00
## Mean : 0.3084 Mean : 5.419 Mean : 0.0548 Mean : 30.85
## 3rd Qu.: 0.5800 3rd Qu.: 15.900 3rd Qu.: 0.1530 3rd Qu.: 70.00
## Max. : 3.8600 Max. : 141.150 Max. : 1.3510 Max. : 623.00
## NA's :616 NA's :638 NA's :647
## TotalSulfurDioxide Density pH Sulphates
## Min. : -823.0 Min. :0.8881 Min. :0.480 Min. : -3.1300
```

## 1st Qu.:	27.0	1st Qu.:	0.9877	1st Qu.:	2.960	1st Qu.:	0.2800
## Median :	123.0	Median :	0.9945	Median :	3.200	Median :	0.5000
## Mean :	120.7	Mean :	0.9942	Mean :	3.208	Mean :	0.5271
## 3rd Qu.:	208.0	3rd Qu.:	1.0005	3rd Qu.:	3.470	3rd Qu.:	0.8600
## Max. :	1057.0	Max. :	1.0992	Max. :	6.130	Max. :	4.2400
## NA's :	682			NA's :	395	NA's :	1210
## Alcohol		LabelAppeal		AcidIndex		STARS	
## Min. :	-4.70	Min. :	-2.000000	Min. :	4.000	Min. :	1.000
## 1st Qu.:	9.00	1st Qu.:	-1.000000	1st Qu.:	7.000	1st Qu.:	1.000
## Median :	10.40	Median :	0.000000	Median :	8.000	Median :	2.000
## Mean :	10.49	Mean :	-0.009066	Mean :	7.773	Mean :	2.042
## 3rd Qu.:	12.40	3rd Qu.:	1.000000	3rd Qu.:	8.000	3rd Qu.:	3.000
## Max. :	26.50	Max. :	2.000000	Max. :	17.000	Max. :	4.000
## NA's :	653					NA's :	3359

Evaluation:

##	IN	TARGET	FixedAcidity	VolatileAcidity	
## Min. :	3	Mode:logical	Min. : -18.200	Min. : -2.8300	
## 1st Qu.:	4018	NA's:3335	1st Qu.:	5.200	
## Median :	7906		Median :	6.900	
## Mean :	8048		Mean :	6.864	
## 3rd Qu.:	12061		3rd Qu.:	9.000	
## Max. :	16130		Max. :	33.500	
##					
## CitricAcid		ResidualSugar	Chlorides	FreeSulfurDioxide	
## Min. :	-3.1200	Min. : -128.300	Min. : -1.15000	Min. : -563.00	
## 1st Qu.:	0.0000	1st Qu.:	-2.600	1st Qu.:	3.00
## Median :	0.3100	Median :	3.600	Median :	30.00
## Mean :	0.3124	Mean :	5.319	Mean :	34.95
## 3rd Qu.:	0.6050	3rd Qu.:	17.200	3rd Qu.:	79.25
## Max. :	3.7600	Max. :	145.400	Max. :	617.00
##		NA's :	168	NA's :	138
##				NA's :	152
## TotalSulfurDioxide		Density	pH	Sulphates	
## Min. :	-769.00	Min. : 0.8898	Min. : 0.600	Min. : -3.0700	
## 1st Qu.:	27.25	1st Qu.:	0.9883	1st Qu.:	0.3300
## Median :	124.00	Median :	0.9946	Median :	0.5000
## Mean :	123.41	Mean :	0.9947	Mean :	0.5346
## 3rd Qu.:	210.00	3rd Qu.:	1.0005	3rd Qu.:	0.8200
## Max. :	1004.00	Max. :	1.0998	Max. :	4.1800
## NA's :	157			NA's :	104
##				NA's :	310
## Alcohol		LabelAppeal	AcidIndex	STARS	
## Min. :	-4.20	Min. : -2.00000	Min. : 5.000	Min. : 1.00	
## 1st Qu.:	9.00	1st Qu.:	-1.00000	1st Qu.:	1.00
## Median :	10.40	Median :	0.00000	Median :	2.00
## Mean :	10.58	Mean :	0.01349	Mean :	2.04
## 3rd Qu.:	12.50	3rd Qu.:	1.00000	3rd Qu.:	3.00
## Max. :	25.60	Max. :	2.00000	Max. :	4.00
## NA's :	185			NA's :	841

Using the DataExplorer package we use the `create_report` function which pulls a full data profile from our training data set and create an html file with basic statistics, structure, missing data, distribution visualizations, correlation matrix and principal component analysis for our data. You can find these output in our github.

```

# Do not render since it will produce a separate html file
# Remove TARGET from eval report since it will contain all
# NAs and will make the correlation plot fail to render
DataExplorer::create_report(dftrain, output_file = "training_report.html")
DataExplorer::create_report(dfeval %>%
  select(-TARGET), output_file = "eval_report.html")

```

Based on this our training data includes 12795 records and 16 variables whereas the evaluation data includes 3335 records and 16 variables.

Training:

```

## 'data.frame': 12795 obs. of 16 variables:
## $ INDEX : int 1 2 4 5 6 7 8 11 12 13 ...
## $ TARGET : int 3 3 5 3 4 0 0 4 3 6 ...
## $ FixedAcidity : num 3.2 4.5 7.1 5.7 8 11.3 7.7 6.5 14.8 5.5 ...
## $ VolatileAcidity : num 1.16 0.16 2.64 0.385 0.33 0.32 0.29 -1.22 0.27 -0.22 ...
## $ CitricAcid : num -0.98 -0.81 -0.88 0.04 -1.26 0.59 -0.4 0.34 1.05 0.39 ...
## $ ResidualSugar : num 54.2 26.1 14.8 18.8 9.4 ...
## $ Chlorides : num -0.567 -0.425 0.037 -0.425 NA 0.556 0.06 0.04 -0.007 -0.277 ...
## $ FreeSulfurDioxide : num NA 15 214 22 -167 -37 287 523 -213 62 ...
## $ TotalSulfurDioxide: num 268 -327 142 115 108 15 156 551 NA 180 ...
## $ Density : num 0.993 1.028 0.995 0.996 0.995 ...
## $ pH : num 3.33 3.38 3.12 2.24 3.12 3.2 3.49 3.2 4.93 3.09 ...
## $ Sulphates : num -0.59 0.7 0.48 1.83 1.77 1.29 1.21 NA 0.26 0.75 ...
## $ Alcohol : num 9.9 NA 22 6.2 13.7 15.4 10.3 11.6 15 12.6 ...
## $ LabelAppeal : int 0 -1 -1 -1 0 0 0 1 0 0 ...
## $ AcidIndex : int 8 7 8 6 9 11 8 7 6 8 ...
## $ STARS : int 2 3 3 1 2 NA NA 3 NA 4 ...

```

Evaluation:

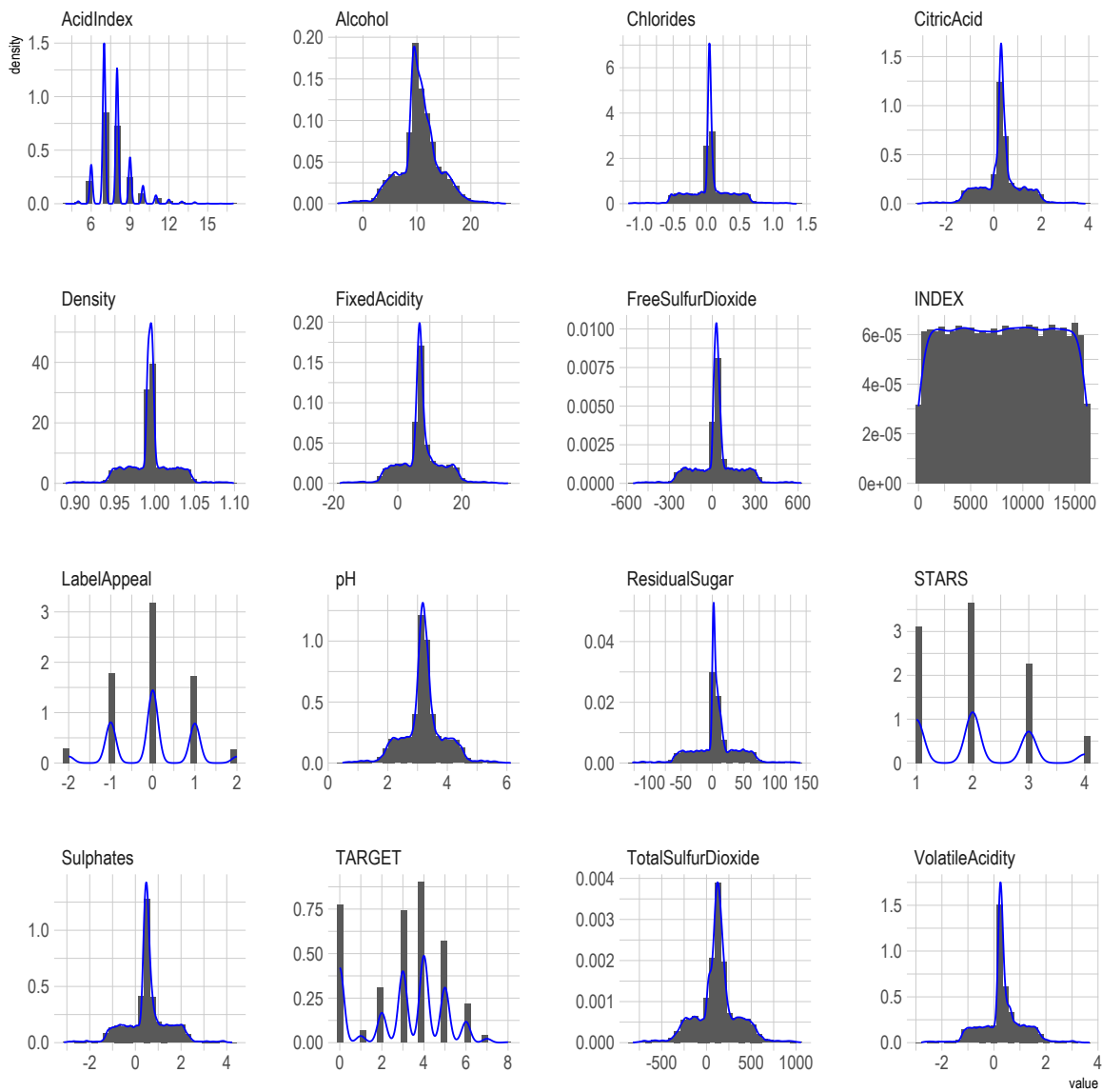
```

## 'data.frame': 3335 obs. of 16 variables:
## $ IN : int 3 9 10 18 21 30 31 37 39 47 ...
## $ TARGET : logi NA NA NA NA NA NA ...
## $ FixedAcidity : num 5.4 12.4 7.2 6.2 11.4 17.6 15.5 15.9 11.6 3.8 ...
## $ VolatileAcidity : num -0.86 0.385 1.75 0.1 0.21 0.04 0.53 1.19 0.32 0.22 ...
## $ CitricAcid : num 0.27 -0.76 0.17 1.8 0.28 -1.15 -0.53 1.14 0.55 0.31 ...
## $ ResidualSugar : num -10.7 -19.7 -33 1 1.2 1.4 4.6 31.9 -50.9 -7.7 ...
## $ Chlorides : num 0.092 1.169 0.065 -0.179 0.038 ...
## $ FreeSulfurDioxide : num 23 -37 9 104 70 -250 10 115 35 40 ...
## $ TotalSulfurDioxide: num 398 68 76 89 53 140 17 381 83 129 ...
## $ Density : num 0.985 0.99 1.046 0.989 1.029 ...
## $ pH : num 5.02 3.37 4.61 3.2 2.54 3.06 3.07 2.99 3.32 4.72 ...
## $ Sulphates : num 0.64 1.09 0.68 2.11 -0.07 -0.02 0.75 0.31 2.18 -0.64 ...
## $ Alcohol : num 12.3 16 8.55 12.3 4.8 11.4 8.5 11.4 -0.5 10.9 ...
## $ LabelAppeal : int -1 0 0 -1 0 1 0 1 0 0 ...
## $ AcidIndex : int 6 6 8 8 10 8 12 7 12 7 ...
## $ STARS : int NA 2 1 1 NA 4 3 NA NA NA ...

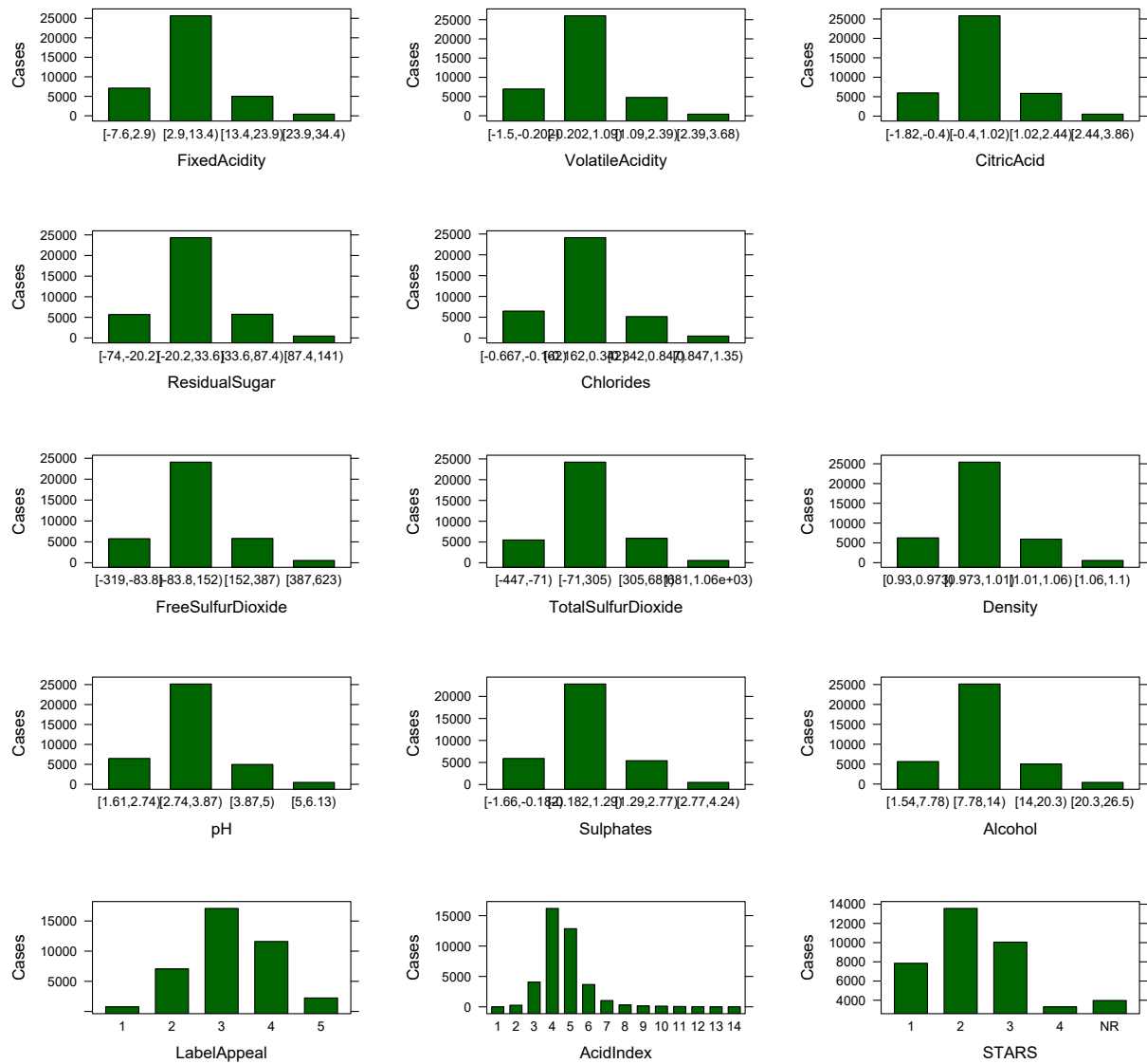
```

Lets take a look at the distribution of each variables in the training data set.

Based on the plots below, we can tell that most of the variables seem to be normally distributed with the exception of AcidIndex and STARS being right skewed. INDEX shows a uniform distribution but has no effect on our data so during the data preparation stage we will be removing it.



The fact that some wines are not rated could be a potential predictor. We'll treat NAs as its own star rating. We'll also look at the number of cases of wine sold against the predictors.



As shown, more cases of wine are sold for mid-range values of all categories of acidity, sugar, chlorides, the dioxides, density, pH, sulphates, and alcohol. Surprisingly, more cases were sold for labels that had mid-range label appeal. A lower acid index seemed to indicate more cases sold. And more cases were sold for wines rated only two stars, indicating that consumers may consider higher-starred wines as too pricey.

Data Preparation:

Data preparation was performed on both the training and evaluation data sets but will only be displayed for the training data. We'll also need to removing the INDEX variable.

Now we'll impute missing values using R's Multiple Imputation by Chained Equations (MICE) package. We'll avoid imputing the STARS variable as the absence of a star rating may be a significant predictor.

```
##
## iter imp variable
## 1 1 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 1 2 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 1 3 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 1 4 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 1 5 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 2 1 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 2 2 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 2 3 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 2 4 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 2 5 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 3 1 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 3 2 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 3 3 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 3 4 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 3 5 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 4 1 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 4 2 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 4 3 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 4 4 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 4 5 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 5 1 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 5 2 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 5 3 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 5 4 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 5 5 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol

##
## iter imp variable
## 1 1 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 1 2 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 1 3 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 1 4 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 1 5 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 2 1 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 2 2 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 2 3 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 2 4 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 2 5 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 3 1 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 3 2 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 3 3 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 3 4 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 3 5 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
## 4 1 ResidualSugar Chlorides FreeSulfurDioxide TotalSulfurDioxide pH Sulphates Alcohol
```


##	4	2	ResidualSugar	Chlorides	FreeSulfurDioxide	TotalSulfurDioxide	pH	Sulphates	Alcohol
##	4	3	ResidualSugar	Chlorides	FreeSulfurDioxide	TotalSulfurDioxide	pH	Sulphates	Alcohol
##	4	4	ResidualSugar	Chlorides	FreeSulfurDioxide	TotalSulfurDioxide	pH	Sulphates	Alcohol
##	4	5	ResidualSugar	Chlorides	FreeSulfurDioxide	TotalSulfurDioxide	pH	Sulphates	Alcohol
##	5	1	ResidualSugar	Chlorides	FreeSulfurDioxide	TotalSulfurDioxide	pH	Sulphates	Alcohol
##	5	2	ResidualSugar	Chlorides	FreeSulfurDioxide	TotalSulfurDioxide	pH	Sulphates	Alcohol
##	5	3	ResidualSugar	Chlorides	FreeSulfurDioxide	TotalSulfurDioxide	pH	Sulphates	Alcohol
##	5	4	ResidualSugar	Chlorides	FreeSulfurDioxide	TotalSulfurDioxide	pH	Sulphates	Alcohol
##	5	5	ResidualSugar	Chlorides	FreeSulfurDioxide	TotalSulfurDioxide	pH	Sulphates	Alcohol

Lets look at another summary to make sure there aren't any NAs where we're not expecting them.

Training data:

##	TARGET	FixedAcidity	VolatileAcidity	CitricAcid
##	Min. :0.000	Min. :-18.100	Min. :-2.7900	Min. :-3.2400
##	1st Qu.:2.000	1st Qu.: 5.200	1st Qu.: 0.1300	1st Qu.: 0.0300
##	Median :3.000	Median : 6.900	Median : 0.2800	Median : 0.3100
##	Mean :3.029	Mean : 7.076	Mean : 0.3241	Mean : 0.3084
##	3rd Qu.:4.000	3rd Qu.: 9.500	3rd Qu.: 0.6400	3rd Qu.: 0.5800
##	Max. :8.000	Max. : 34.400	Max. : 3.6800	Max. : 3.8600
##	ResidualSugar	Chlorides	FreeSulfurDioxide	TotalSulfurDioxide
##	Min. :-127.800	Min. :-1.17100	Min. :-555.00	Min. :-823.0
##	1st Qu.: -2.100	1st Qu.: -0.02900	1st Qu.: -1.00	1st Qu.: 27.0
##	Median : 3.900	Median : 0.04600	Median : 30.00	Median : 124.0
##	Mean : 5.428	Mean : 0.05525	Mean : 30.84	Mean : 120.7
##	3rd Qu.: 16.000	3rd Qu.: 0.15250	3rd Qu.: 70.00	3rd Qu.: 208.0
##	Max. : 141.150	Max. : 1.35100	Max. : 623.00	Max. : 1057.0
##	Density	pH	Sulphates	Alcohol
##	Min. :0.8881	Min. :0.480	Min. :-3.1300	Min. :-4.70
##	1st Qu.:0.9877	1st Qu.:2.960	1st Qu.: 0.2800	1st Qu.: 9.00
##	Median :0.9945	Median :3.200	Median : 0.5000	Median :10.40
##	Mean :0.9942	Mean :3.208	Mean : 0.5269	Mean :10.49
##	3rd Qu.:1.0005	3rd Qu.:3.470	3rd Qu.: 0.8600	3rd Qu.:12.40
##	Max. :1.0992	Max. :6.130	Max. : 4.2400	Max. :26.50
##	LabelAppeal	AcidIndex	STARS	
##	Min. :-2.000000	Min. : 4.000	Length:12795	
##	1st Qu.: -1.000000	1st Qu.: 7.000	Class :character	
##	Median : 0.000000	Median : 8.000	Mode :character	
##	Mean :-0.009066	Mean : 7.773		
##	3rd Qu.: 1.000000	3rd Qu.: 8.000		
##	Max. : 2.000000	Max. :17.000		

Evaluation data:

##	FixedAcidity	VolatileAcidity	CitricAcid	ResidualSugar
##	Min. :-18.200	Min. :-2.8300	Min. :-3.1200	Min. :-128.300
##	1st Qu.: 5.200	1st Qu.: 0.0800	1st Qu.: 0.0000	1st Qu.: -2.600
##	Median : 6.900	Median : 0.2800	Median : 0.3100	Median : 3.600
##	Mean : 6.864	Mean : 0.3103	Mean : 0.3124	Mean : 5.225
##	3rd Qu.: 9.000	3rd Qu.: 0.6300	3rd Qu.: 0.6050	3rd Qu.: 17.150
##	Max. : 33.500	Max. : 3.6100	Max. : 3.7600	Max. : 145.400

```
## Chlorides      FreeSulfurDioxide TotalSulfurDioxide      Density
## Min.      :-1.1500 Min.      :-563.00 Min.      :-769.0 Min.      :0.8898
## 1st Qu.: 0.0155 1st Qu.: 3.00 1st Qu.: 28.0 1st Qu.:0.9883
## Median : 0.0470 Median : 29.00 Median : 124.0 Median :0.9946
## Mean : 0.0624 Mean : 34.34 Mean : 123.9 Mean :0.9947
## 3rd Qu.: 0.1740 3rd Qu.: 79.00 3rd Qu.: 210.0 3rd Qu.:1.0005
## Max. : 1.2630 Max. : 617.00 Max. :1004.0 Max. :1.0998
## pH            Sulphates            Alcohol            LabelAppeal
## Min.      :0.600 Min.      :-3.0700 Min.      :-4.20 Min.      :-2.00000
## 1st Qu.:2.980 1st Qu.: 0.3300 1st Qu.: 9.00 1st Qu.: -1.00000
## Median :3.210 Median : 0.5000 Median :10.40 Median : 0.00000
## Mean :3.235 Mean : 0.5326 Mean :10.59 Mean : 0.01349
## 3rd Qu.:3.480 3rd Qu.: 0.8150 3rd Qu.:12.50 3rd Qu.: 1.00000
## Max. :6.210 Max. : 4.1800 Max. :25.60 Max. : 2.00000
## AcidIndex      STARS              TARGET
## Min.      : 5.000 Length:3335 Mode:logical
## 1st Qu.: 7.000 Class :character NA's:3335
## Median : 8.000 Mode :character
## Mean : 7.748
## 3rd Qu.: 8.000
## Max. :17.000
```

Build Models:

Based on the data, we'll try two model types: a poisson general linear model and a Gaussian multiple linear model.

Poisson Models:

- Poisson Model 1

```
##
## Call:
## glm(formula = TARGET ~ ., family = "poisson", data = cleandf)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -3.2780  -0.6619  -0.0015   0.4504   3.7616
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    1.880e+00  1.951e-01   9.636 < 2e-16 ***
## FixedAcidity     5.726e-05  8.196e-04   0.070 0.944295
## VolatileAcidity  -3.058e-02  6.528e-03  -4.684 2.81e-06 ***
## CitricAcid       4.970e-03  5.896e-03   0.843 0.399265
## ResidualSugar    7.227e-05  1.507e-04   0.479 0.631607
## Chlorides       -4.361e-02  1.609e-02  -2.710 0.006735 **
## FreeSulfurDioxide 9.543e-05  3.402e-05   2.805 0.005034 **
## TotalSulfurDioxide 8.066e-05  2.215e-05   3.641 0.000271 ***
```

```
## Density          -2.730e-01  1.918e-01  -1.423  0.154601
## pH               -1.289e-02  7.550e-03  -1.707  0.087742 .
## Sulphates        -1.284e-02  5.474e-03  -2.346  0.018956 *
## Alcohol           3.470e-03  1.375e-03   2.523  0.011626 *
## LabelAppeal       1.595e-01  6.127e-03  26.031  < 2e-16 ***
## AcidIndex        -7.973e-02  4.573e-03 -17.434  < 2e-16 ***
## STARS2            3.220e-01  1.434e-02  22.454  < 2e-16 ***
## STARS3            4.405e-01  1.562e-02  28.203  < 2e-16 ***
## STARS4            5.556e-01  2.167e-02  25.640  < 2e-16 ***
## STARSNR           -7.666e-01  1.954e-02 -39.234  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
## Null deviance: 22861 on 12794 degrees of freedom
## Residual deviance: 13647 on 12777 degrees of freedom
## AIC: 45625
##
## Number of Fisher Scoring iterations: 6
```

- Poisson Model with stepwise AIC approach

```
##
## Call:
## glm(formula = TARGET ~ VolatileAcidity + Chlorides + FreeSulfurDioxide +
## TotalSulfurDioxide + Density + pH + Sulphates + Alcohol +
## LabelAppeal + AcidIndex + STARS, family = "poisson", data = cleandf)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -3.2803  -0.6604  -0.0027   0.4510   3.7603
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    1.882e+00  1.951e-01   9.646 < 2e-16 ***
## VolatileAcidity -3.071e-02  6.527e-03  -4.706 2.53e-06 ***
## Chlorides       -4.380e-02  1.609e-02  -2.721 0.006503 **
## FreeSulfurDioxide  9.585e-05  3.402e-05   2.817 0.004842 **
## TotalSulfurDioxide 8.085e-05  2.214e-05   3.651 0.000261 ***
## Density        -2.750e-01  1.918e-01  -1.434 0.151591
## pH              -1.280e-02  7.548e-03  -1.696 0.089814 .
## Sulphates       -1.289e-02  5.472e-03  -2.355 0.018525 *
## Alcohol          3.487e-03  1.375e-03   2.536 0.011209 *
## LabelAppeal      1.595e-01  6.127e-03  26.040 < 2e-16 ***
## AcidIndex       -7.945e-02  4.518e-03 -17.585 < 2e-16 ***
## STARS2           3.222e-01  1.434e-02  22.475 < 2e-16 ***
## STARS3           4.405e-01  1.562e-02  28.210 < 2e-16 ***
## STARS4           5.558e-01  2.167e-02  25.650 < 2e-16 ***
## STARSNR          -7.668e-01  1.954e-02 -39.244 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
```

```
##
## Null deviance: 22861 on 12794 degrees of freedom
## Residual deviance: 13648 on 12780 degrees of freedom
## AIC: 45620
##
## Number of Fisher Scoring iterations: 6
```

Multiple Linear Regression Models:

- MLR Model 1

```
##
## Call:
## lm(formula = TARGET ~ ., data = cleandf)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4.8479 -0.8590  0.0251  0.8458  6.1615
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    5.056e+00  4.419e-01  11.440 < 2e-16 ***
## FixedAcidity    5.629e-04  1.858e-03   0.303 0.761966
## VolatileAcidity -9.472e-02  1.477e-02  -6.412 1.49e-10 ***
## CitricAcid      1.700e-02  1.343e-02   1.266 0.205593
## ResidualSugar   2.473e-04  3.420e-04   0.723 0.469637
## Chlorides      -1.337e-01  3.640e-02  -3.673 0.000241 ***
## FreeSulfurDioxide 2.829e-04  7.758e-05   3.647 0.000266 ***
## TotalSulfurDioxide 2.317e-04  4.984e-05   4.648 3.39e-06 ***
## Density        -7.980e-01  4.357e-01  -1.831 0.067053 .
## pH             -3.304e-02  1.706e-02  -1.937 0.052746 .
## Sulphates      -3.394e-02  1.239e-02  -2.740 0.006147 **
## Alcohol         1.156e-02  3.114e-03   3.713 0.000205 ***
## LabelAppeal     4.674e-01  1.363e-02  34.299 < 2e-16 ***
## AcidIndex      -1.997e-01  9.097e-03 -21.949 < 2e-16 ***
## STARS2          1.031e+00  3.256e-02  31.671 < 2e-16 ***
## STARS3          1.600e+00  3.765e-02  42.510 < 2e-16 ***
## STARS4          2.292e+00  5.965e-02  38.422 < 2e-16 ***
## STARSNR         -1.361e+00  3.291e-02 -41.369 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.306 on 12777 degrees of freedom
## Multiple R-squared:  0.5412, Adjusted R-squared:  0.5406
## F-statistic: 886.7 on 17 and 12777 DF, p-value: < 2.2e-16
```

- MLR Model 2

```
##
## Call:
## lm(formula = TARGET ~ VolatileAcidity + Chlorides + FreeSulfurDioxide +
##      TotalSulfurDioxide + Density + pH + Sulphates + Alcohol +
##      LabelAppeal + AcidIndex + STARS, data = cleandf)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4.8483 -0.8620  0.0239  0.8436  6.1561
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    5.064e+00  4.419e-01  11.460 < 2e-16 ***
## VolatileAcidity -9.509e-02  1.477e-02  -6.438 1.25e-10 ***
## Chlorides      -1.344e-01  3.640e-02  -3.693 0.000223 ***
## FreeSulfurDioxide  2.848e-04  7.756e-05   3.672 0.000241 ***
## TotalSulfurDioxide 2.328e-04  4.983e-05   4.672 3.02e-06 ***
## Density        -8.060e-01  4.357e-01  -1.850 0.064311 .
## pH             -3.300e-02  1.706e-02  -1.935 0.053009 .
## Sulphates      -3.414e-02  1.238e-02  -2.757 0.005835 **
## Alcohol         1.158e-02  3.113e-03   3.722 0.000199 ***
## LabelAppeal     4.674e-01  1.363e-02  34.302 < 2e-16 ***
## AcidIndex      -1.984e-01  8.939e-03 -22.198 < 2e-16 ***
## STARS2          1.032e+00  3.255e-02  31.702 < 2e-16 ***
## STARS3          1.601e+00  3.764e-02  42.525 < 2e-16 ***
## STARS4          2.293e+00  5.965e-02  38.441 < 2e-16 ***
## STARSNR        -1.362e+00  3.290e-02 -41.384 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.306 on 12780 degrees of freedom
## Multiple R-squared:  0.5411, Adjusted R-squared:  0.5406
## F-statistic: 1077 on 14 and 12780 DF, p-value: < 2.2e-16
```

Select Models:

In this section, an optimal model will be selected based on its performance when trained on the data. To select the models, we'll use AIC and MSE to measure accuracy of the predicted values.

Below, the Poisson and Multiple Linear Regression models have been compared to select the model with the lowest AIC.

Comparison of Poisson Models:

We'll need to compare the AIC's of each Poisson Model.

Poisson Model 1:

```
## [1] 45625.22
```

Poisson Model 2:

```
## [1] 45620.16
```

Poisson Model 2 proves to have the lower AIC of the two, with a 33947.74 AIC. Below is the formula for Poisson Model 2.

```
## [[1]]
## TARGET ~ VolatileAcidity + Chlorides + FreeSulfurDioxide + TotalSulfurDioxide +
##      Density + pH + Sulphates + Alcohol + LabelAppeal + AcidIndex +
##      STARS
```

Comparision of Multiple Linar Models:

We'll need to compare the Adjusted R Squares of each Linear Model.

Linear Model 1:

```
## [1] 0.5406183
```

Linear Model 2:

```
## [1] 0.5406471
```

Linear Model 2 proves to have the higher Adjusted R Squares, with a value of 0.4544041. Below is the formula for Linear Model 2.

```
## [[1]]
## TARGET ~ VolatileAcidity + Chlorides + FreeSulfurDioxide + TotalSulfurDioxide +
##      Density + pH + Sulphates + Alcohol + LabelAppeal + AcidIndex +
##      STARS
```

Mean Square Error:

The Mean Square Error measures the averaged square different between the estimated values and the actual value. The lower the value of the MSE, the more accurately the model is able to predict the values.

$$\text{MSE} = \frac{1}{n} \sum (y - \hat{y})^2$$

Comparison of Possion and Gaussian Linear Models:

By evaluating the AIC's and MSE's of each model, we can choose the best one be looking at the lowest AIC and lowest MSE.

	Possion Model 1	Possion Model 2	Linear Model 1	Linear Model 2
MSE	6.7060661648579	6.70614723918115	1.70471690181985	1.70461008756085
AIC	45625.2226362434	45620.1579756524	43155.4653254402	43151.6674641144

Based on the above, the linear model has better model statistics than the poisson model.

Prediction from optimal multiple linear regression model:

```
## # A tibble: 10 x 15
##   Fixed~1 Volat~2 Citri~3 Resid~4 Chlor~5 FreeS~6 Total~7 Density pH Sulph~8
##   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1     5.4 -0.86  0.27 -10.7  0.092    23   398  0.985  5.02  0.64
## 2    12.4  0.385 -0.76 -19.7  1.17   -37    68  0.990  3.37  1.09
## 3     7.2  1.75  0.17 -33    0.065    9    76  1.05  4.61  0.68
## 4     6.2  0.1   1.8   1    -0.179  104   89  0.989  3.2   2.11
## 5    11.4  0.21  0.28  1.2  0.038    70   53  1.03  2.54 -0.07
## 6    17.6  0.04 -1.15  1.4  0.535  -250  140  0.950  3.06 -0.02
## 7    15.5  0.53 -0.53  4.6  1.26    10    17  1.00  3.07  0.75
## 8    15.9  1.19  1.14  31.9 -0.299   115  381  1.03  2.99  0.31
## 9    11.6  0.32  0.55 -50.9  0.076    35    83  1.00  3.32  2.18
## 10     3.8  0.22  0.31 -7.7  0.039    40   129  0.906  4.72 -0.64
## # ... with 5 more variables: Alcohol <dbl>, LabelAppeal <int>, AcidIndex <int>,
## #   STARS <chr>, TARGET <dbl>, and abbreviated variable names 1: FixedAcidity,
## #   2: VolatileAcidity, 3: CitricAcid, 4: ResidualSugar, 5: Chlorides,
## #   6: FreeSulfurDioxide, 7: TotalSulfurDioxide, 8: Sulphates
```

Appendix:

```
# load libraries
library(tidyverse)
library(dplyr)
library(corrplot)
library(skimr)
library(DataExplorer)
library(ggplot2)
library(hrbrthemes)
library(mice)

# load data
dftrain <- read.csv("https://raw.githubusercontent.com/letisalba/Data_621/master/Homework_5/csv/wine-tr")
dfeval <- read.csv("https://raw.githubusercontent.com/letisalba/Data_621/master/Homework_5/csv/wine-eval")
head(dftrain)

# summary of training and evaluation data sets
summary(dftrain)
summary(dfeval)

# Do not render since it will produce a separate html file
# Remove TARGET from eval report since it will contain all
# NAs and will make the correlation plot fail to render
DataExplorer::create_report(dftrain, output_file = "training_report.html")
DataExplorer::create_report(dfeval %>%
  select(-TARGET), output_file = "eval_report.html")

# structure of training and evaluation data
str(dftrain)
str(dfeval)
```

```

# plotting distribution of training data
plot_train <- dftrain %>%
  gather(key = "variable", value = "value")

ggplot(plot_train) + geom_histogram(aes(x = value, y = ..density..),
  bins = 30) + geom_density(aes(x = value), color = "blue") +
  theme_ipsum() + facet_wrap(. ~ variable, scales = "free",
  ncol = 4)

# Create logical variable to indicate whether there is a
# star rating for this wine
dftrain <- dftrain %>%
  mutate(STARS = ifelse(is.na(STARS), "NR", STARS))
dfeval <- dfeval %>%
  mutate(STARS = ifelse(is.na(STARS), "NR", STARS))

# Look at the number of cases of wine sold against the
# predictors.
plt <- vector("list", ncol(dftrain) - 1)
for (i in seq(3, 16)) {
  # skip INDEX and TARGET variables
  if (class(dftrain[, i]) == "numeric") {
    tmpmin <- min(dftrain[, i], na.rm = T)
    tmpinterval <- (max(dftrain[, i], na.rm = T) - tmpmin)/5
    tmpcuts <- c()
    for (j in seq(1, 5)) {
      tmpcuts <- c(tmpcuts, tmpmin + (j * tmpinterval))
    }
    # dftrain$x <- dftrain[, i] %>% cut(breaks=5,
    # ordered_result=T, right=F)
    dftrain$x <- dftrain[, i] %>%
      cut(breaks = tmpcuts, ordered_result = T, right = F)
  } else {
    dftrain$x <- dftrain[, i]
  }
  dftmp <- dftrain %>%
    group_by(x) %>%
    summarize(ct = sum(TARGET))
  plt[[i]] <- barchart(dftmp$ct ~ dftmp$x, horiz = F, col = "darkgreen",
    xlab = colnames(dftrain)[i], ylab = "Cases")
}
dftrain <- subset(dftrain, select = -x) # remove temporary variable
grid.arrange(grobs = plt[3:7], ncol = 3, nrow = 2)
grid.arrange(grobs = plt[8:13], ncol = 3, nrow = 2)
grid.arrange(grobs = plt[14:16], ncol = 3, nrow = 2)

# Removing INDEX from training and eval data For some
# reason R renamed the INDEX column to 'i..INDEX'
dftrain <- dftrain %>%
  dplyr::select(-i..INDEX)
dfeval <- dfeval %>%
  dplyr::select(-IN)

```



```

# Impute missing values in training data
dftrain_imputed <- mice(dftrain, m = 5, maxit = 5, method = "pmm")
cleandf <- complete(dftrain_imputed) %>%
  mutate(STARS = dftrain$STARS)

# Impute missing values in eval data (except for TARGET)
dfeval_imputed <- mice(dfeval %>%
  select(-TARGET), m = 5, maxit = 5, method = "pmm")
cleandf_eval <- complete(dfeval_imputed) %>%
  mutate(STARS = dfeval$STARS, TARGET = dfeval$TARGET)

# Look at another summary to make sure there aren't any NAs
# where we're not expecting them
summary(cleandf)
summary(cleandf_eval)

# Poisson model
p_mod1 <- glm(TARGET ~ ., family = "poisson", data = cleandf)
summary(p_mod1)

# Poisson Model with stepwise AIC approach
p_mod2 <- stepAIC(p_mod1, trace = F)
summary(p_mod2)

# Multiple Linear Regression Models:

# MLR Model 1
lm_mod1 <- lm(TARGET ~ ., data = cleandf)
aic_lm_mod1 = AIC(lm_mod1)
summary(lm_mod1)

# MLR Model 2
lm_mod2 <- stepAIC(lm_mod1, trace = F)
aic_lm_mod2 = AIC(lm_mod2)
summary(lm_mod2)

# Select Models:

# Comparison of Poisson Models:

# Poisson Model 1:
aic_p_mod1 <- p_mod1$aic
aic_p_mod1

# Poisson Model 2:
aic_p_mod2 <- p_mod2$aic
aic_p_mod2

# Poisson - Minimum AIC
c(p_mod1$formula, p_mod2$formula)[which.min(c(p_mod1$aic, p_mod2$aic))]

# Comparison of Multiple Linear Models:

```

```

# Linear Model 1:
r2_lm_mod1 <- summary(lm_mod1)$adj.r.squared
r2_lm_mod1

# Linear Model 2:
r2_lm_mod2 <- summary(lm_mod2)$adj.r.squared
r2_lm_mod2

# Multiple Linear Regression Model - Highest Adjusted R
# Squared
c(formula(lm_mod1), formula(lm_mod2))[which.max(c(summary(lm_mod1)$adj.r.squared,
summary(lm_mod2)$adj.r.squared))]

# Mean Square Error:
mse <- function(df, model) {
  mean((df$TARGET - predict(model))^2)
}
mse_p_mod1 <- mse(cleandf, p_mod1)
mse_p_mod2 <- mse(cleandf, p_mod2)
mse_lm_mod1 <- get_mse(lm_mod1)
mse_lm_mod2 <- get_mse(lm_mod2)

# Comparison of Poisson and Negative Binomial Model's:
models <- c("Poisson Model 1", "Poisson Model 2", "Linear Model 1",
"Linear Model 2")
# rows <- c('Models', 'MSE', 'AIC')
MSE <- list(mse_p_mod1, mse_p_mod2, mse_lm_mod1, mse_lm_mod2)
AIC <- list(aic_p_mod1, aic_p_mod2, aic_lm_mod1, aic_lm_mod2)
knitr::kable(rbind(MSE, AIC), col.names = models)

# Prediction from optimal multiple linear regression model
prob2 <- predict(lm_mod2, cleandf_eval, interval = "prediction")
cleandf_eval$TARGET <- prob2[, 1]
cleandf_eval %>%
  head(10) %>%
  as_tibble()
write.csv(cleandf_eval, "wine_predictions2.csv", row.names = FALSE)

```

References:

<https://englianhu.files.wordpress.com/2016/01/faraway-extending-the-linear-model-with-r-e28093-2006.pdf>