Beer and Breweries Case Study

Matt Sherga & Rudranil Mitra

6/22/2020

Load the libraries

```
# Load the libraries in R
library(XML) #xml_Parse
library(dplyr)
library(tidyr)
library(stringr)
library(rvest) #html_table, html_node
library(ggplot2)
library(RCurl) #getURL
library(tidyverse)
library(BSDA)
library(GGally)
library(openintro)
library(viridis)
library(mapproj)
library(ggpubr)
library(FSA)
```

```
# Load the dataset from the file system
beers<- read.csv(file.choose(),na.strings=c("","NA"))
brews<- read.csv(file.choose(),na.strings=c("","NA"))
```

How many breweries are present in each state

We can see that Colorado, California, Michigan, Oregon and Texas have the highest number of breweries.

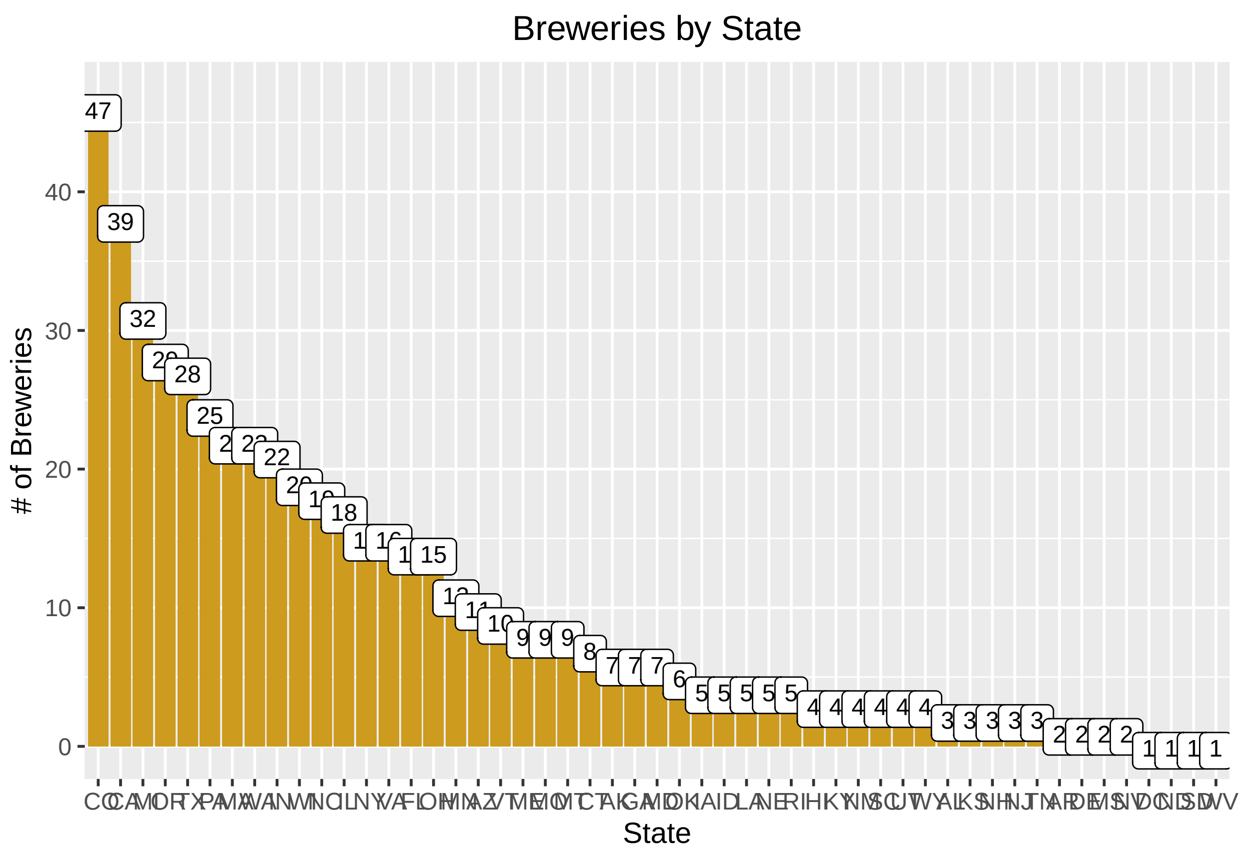
West Virginia & DC only have one brewery each

```
#Q1 breweries per state
#Group the data by state
brewbystate<- data.frame(brews %>% group_by(State) %>% tally() %>% arrange(desc(n)))
#Print the data to show the brewery count per state
print(brewbystate)
```

```
##    State  n
## 1     CO 47
## 2     CA 39
## 3     MI 32
## 4     OR 29
## 5     TX 28
## 6     PA 25
```

```
## 7     MA 23
## 8     WA 23
## 9     IN 22
## 10    WI 20
## 11    NC 19
## 12    IL 18
## 13    NY 16
## 14    VA 16
## 15    FL 15
## 16    OH 15
## 17    MN 12
## 18    AZ 11
## 19    VT 10
## 20    ME  9
## 21    MO  9
## 22    MT  9
## 23    CT  8
## 24    AK  7
## 25    GA  7
## 26    MD  7
## 27    OK  6
## 28    IA  5
## 29    ID  5
## 30    LA  5
## 31    NE  5
## 32    RI  5
## 33    HI  4
## 34    KY  4
## 35    NM  4
## 36    SC  4
## 37    UT  4
## 38    WY  4
## 39    AL  3
## 40    KS  3
## 41    NH  3
## 42    NJ  3
## 43    TN  3
## 44    AR  2
## 45    DE  2
## 46    MS  2
## 47    NV  2
## 48    DC  1
## 49    ND  1
## 50    SD  1
## 51    WV  1
```

```r
#Plot the data using GGPlot
brewbystate %>% ggplot(aes(x = reorder(as.factor(State),-n), y = n)) +
  labs(y="# of Breweries", x = "State") +
  geom_bar(stat = "identity", position = "dodge", fill = "goldenrod3") +
  geom_label(size = 3, label = brewbystate$n, vjust = 1) +
  ggtitle('Breweries by State') + theme(plot.title = element_text(hjust = .5))
```



Merge the data sets and print first/last 6 rows

```
#Q2 merge the data sets and print first/last 6 rows.
#rename brewery id column to match "beers" respective column.
names(brews)[1] <- "Brewery_id"

#rename columns from each df since they are names for different things.
names(beers)[1]<- "Beer"
names(brews)[2]<- "Brewery"

#merge both the datasets
brewerydata<- merge(beers,brews, by = "Brewery_id", all = TRUE)
brewerydata$State<-as.factor(brewerydata$State)
brewerydata$City<-as.factor(brewerydata$City)
brewerydata$Brewery_id<-as.factor(brewerydata$Brewery_id)
brewerydata$ABV<-brewerydata$ABV * 100
brewerydata<-brewerydata %>% rename("% ABV" = ABV)

#Print the first and the last 6 records in the dataset
head(brewerydata, 6)
```

```
##   Brewery_id          Beer Beer_ID % ABV IBU
## 1          1  Get Together    2692   4.5  50
## 2          1 Maggie's Leap    2691   4.9  26
## 3          1    Wall's End    2690   4.8  19
```

```
## 4          1       Pumpion    2689   6.0  38
## 5          1    Stronghold    2688   6.0  25
## 6          1   Parapet ESB    2687   5.6  47
##                                  Style Ounces            Brewery        City
## 1                          American IPA     16 NorthGate Brewing  Minneapolis
## 2                    Milk / Sweet Stout     16 NorthGate Brewing  Minneapolis
## 3                     English Brown Ale     16 NorthGate Brewing  Minneapolis
## 4                           Pumpkin Ale     16 NorthGate Brewing  Minneapolis
## 5                       American Porter     16 NorthGate Brewing  Minneapolis
## 6 Extra Special / Strong Bitter (ESB)     16 NorthGate Brewing  Minneapolis
##   State
## 1    MN
## 2    MN
## 3    MN
## 4    MN
## 5    MN
## 6    MN
```

```r
tail(brewerydata, 6)
```

```
##      Brewery_id                      Beer Beer_ID % ABV IBU
## 2405        556             Pilsner Ukiah      98   5.5  NA
## 2406        557  Heinnieweisse Weissebier      52   4.9  NA
## 2407        557           Snapperhead IPA      51   6.8  NA
## 2408        557         Moo Thunder Stout      50   4.9  NA
## 2409        557         Porkslap Pale Ale      49   4.3  NA
## 2410        558 Urban Wilderness Pale Ale      30   4.9  NA
##                         Style Ounces                    Brewery          City
## 2405          German Pilsener     12        Ukiah Brewing Company         Ukiah
## 2406               Hefeweizen     12      Butternuts Beer and Ale Garrattsville
## 2407             American IPA     12      Butternuts Beer and Ale Garrattsville
## 2408       Milk / Sweet Stout     12      Butternuts Beer and Ale Garrattsville
## 2409 American Pale Ale (APA)     12      Butternuts Beer and Ale Garrattsville
## 2410        English Pale Ale     12 Sleeping Lady Brewing Company     Anchorage
##      State
## 2405    CA
## 2406    NY
## 2407    NY
## 2408    NY
## 2409    NY
## 2410    AK
```

Address the missing values in each column

ABV had 62 missing values

IBU had 1005 missing values

Style of beer had 5 missing values

Our initial approach was to scrape the web to find the missing values for ABV & IBU. However we encountered quite a few challenges in extracting the data from the internet due to inconsistencies in HTML formatting across different websites. Our final approach was to calculate the median values of ABV and IBU per style and impute them into the respective missing values.

```r
#Q3 Address the missing values
#how many na rows in ABV and IBU? What about missing Styles?
length(which(is.na(brewerydata$`% ABV`))) #62 NAs
```

```
## [1] 62
```

```r
length(which(is.na(brewerydata$IBU))) #1005 NAs
```

```
## [1] 1005
```

```r
length(which(is.na(brewerydata$Style))) #5 NAs
```

```
## [1] 5
```

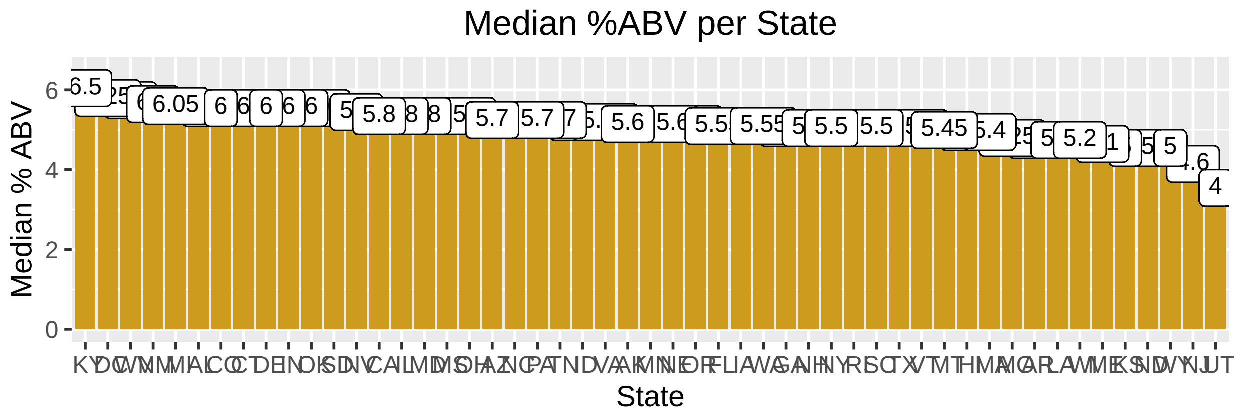
```r
#examined the five rows with View(brewerydata), and found that "CROWLER" is not a beer. It's just a con

#deleting crowler and can'd aid
brewerydata<-brewerydata[-c(227,992, 993),]

#adding style from https://untappd.com/b/freetail-brewing-co-oktoberfiesta/79567
brewerydata$Style[454] <- "Märzen"
#adding style from https://untappd.com/b/four-peaks-brewing-company-kilt-lifter/4055
brewerydata$Style[945] <- "Scottish Export Ale"

#find means per style of ABV and IBU, disregarding NA rows
abvmean <- brewerydata %>% group_by(Style, na.rm = TRUE) %>% mutate(`Mean%ABV` = round(mean(`% ABV`, na

ibumean <- brewerydata %>% group_by(Style) %>% mutate(MeanIBU = as.integer(mean(IBU, na.rm = TRUE)))

#replace NA rows with means for their respective styles taken from above.
brewerydata$`% ABV`[is.na(brewerydata$`% ABV`)] <- abvmean$`Mean%ABV`[is.na(brewerydata$`% ABV`)]

brewerydata$IBU[is.na(brewerydata$IBU)] <- ibumean$MeanIBU[is.na(brewerydata$IBU)]

#52 empty IBU values remain. After looking at each one, there are three that have IBU values according

#add IBU from https://untappd.com/b/thunderhead-brewing-golden-frau/38392
brewerydata$IBU[1476] <- 12
#add IBU from https://untappd.com/b/hawai-i-nui-brewing-southern-cross-belgian-double-red-ale/29698
brewerydata$IBU[1199] <- 59
#add IBU from https://untappd.com/b/figueroa-mountain-brewing-co-weiss-weiss-baby/1043342
brewerydata$IBU[273] <- 40
```

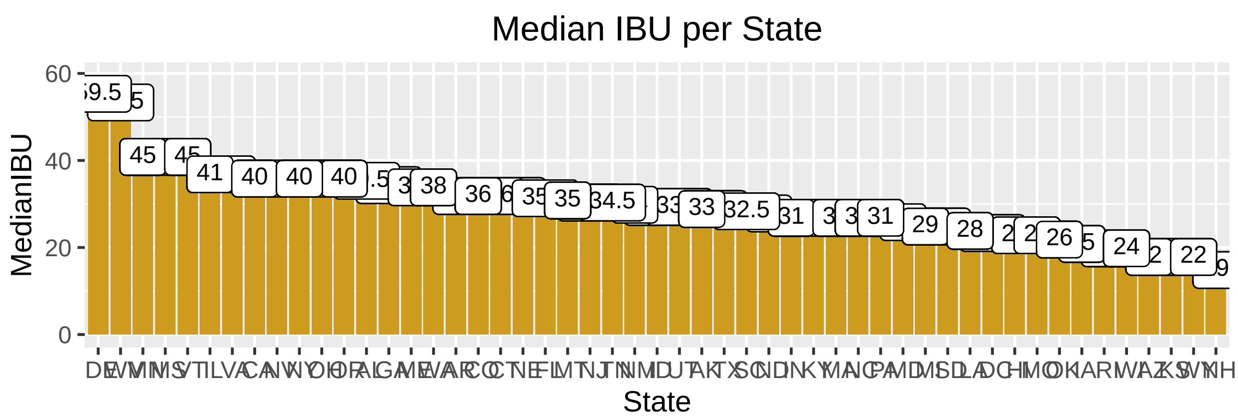
Plots for Median ABV and IBU by State

DC in top 5 median ABV, WV in top 5 ABV & IBU. Untapped markets for lower alcohol beers.

```r
#Q4 Medians of ABV and IBU

#find median of non-NA IBUs by state
brewerydata<- brewerydata %>%
  group_by(State) %>%
  mutate(MedianIBU = median(IBU, na.rm = TRUE))

#find median of non-NA ABVs by state
```

```r
brewerydata<- brewerydata %>%
  group_by(State) %>%
  mutate(MedianABV = median(`% ABV`, na.rm = TRUE))

## Make adjustments to the scale of the text

####plot results####
#plot the median ABVs for each state, with labels
medabvplot<- brewerydata %>% ggplot(aes(x = reorder(State,-MedianABV), y = MedianABV)) +
  ylab("Median % ABV") +
  xlab('State') +
  geom_bar(stat = "identity", position = "dodge", fill = "goldenrod3") +
  geom_label(size = 3, label = brewerydata$MedianABV, vjust = 1) +
  theme(plot.title = element_text(hjust = .5)) +
  labs(title = "Median %ABV per State")

#plot the median IBUs for each state, with labels
medibuplot<- brewerydata %>% ggplot(aes(x = reorder(State,-MedianIBU), y = MedianIBU), ylab = "Median I
  geom_bar(stat = "identity", position = "dodge", fill = "goldenrod3") +
  geom_label(size = 3, label = brewerydata$MedianIBU, vjust = 1)+
  theme(plot.title = element_text(hjust = .5))+
  labs(title = "Median IBU per State") +
  xlab('State')

#plots both charts together in a stacked configuration
ggarrange(medabvplot, medibuplot, ncol = 1, nrow = 2)
```





Which state has the maximum alcoholic (ABV) beer? Which state has the most bitter (IBU) beer?

Colorado is the state with highest ABV

Oregon is the state with highest IBU

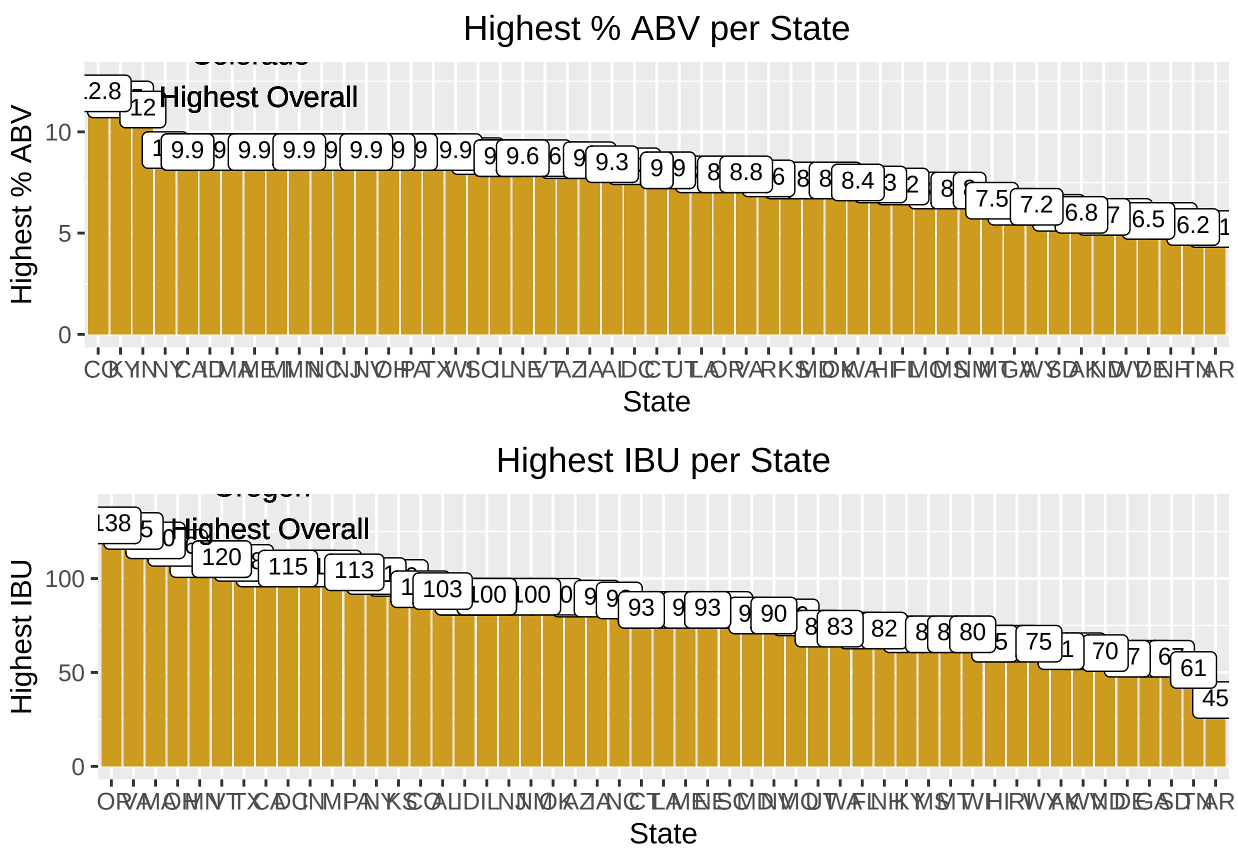
Highest ABV = 12.8 %

Highest IBU = 138

Colorado Highest ABV, and higher-end IBU at 103.

```
#Q5

#Look up and store max values per state, making sure to ignore NA values
maxabvperstate<-brewerydata %>%
  group_by(State) %>%
  filter(`% ABV`==max(`% ABV`, na.rm = TRUE))

maxibuperstate<-brewerydata %>%
  group_by(State) %>%
  filter(IBU==max(IBU, na.rm = TRUE))

#discover which state has the highest for each
maxabvstate<-brewerydata$State[which.max(brewerydata$`% ABV`)] #Colorado (CO)
maxibustate<-brewerydata$State[which.max(brewerydata$IBU)] #Oregon (OR)
```

```r
#plot max ABVs per state, label them, and call out the highest one
maxabvplot<- maxabvperstate %>% ggplot(aes(x = reorder(State,-maxabvperstate$'% ABV'), y = `% ABV`)) +
  ylab("Highest % ABV") +
  geom_bar(stat = "identity", position = "dodge", fill = "goldenrod3") +
  geom_label(size = 3, label = maxabvperstate$`% ABV`, vjust = 1) +
  theme(plot.title = element_text(hjust = .5)) +
  labs(title = "Highest % ABV per State") +
  xlab('State') +
  geom_text(aes(8, 12.8, label="Colorado \n Highest Overall"))

#plot max IBUs per state, label them, and call out the highest one
maxibuplot<- maxibuperstate %>% ggplot(aes(x = reorder(State,-IBU), y = IBU)) +
  ylab("Highest IBU") +
  geom_bar(stat = "identity", position = "dodge", fill = "goldenrod3") +
  geom_label(size = 3, label = maxibuperstate$IBU, vjust = 1) +
  theme(plot.title = element_text(hjust = .5)) +
  labs(title = "Highest IBU per State") +
  xlab('State') +
  geom_text(aes(8, 138, label="Oregon \n Highest Overall"))

#plots both charts together in a stacked configuration
ggarrange(maxabvplot, maxibuplot, ncol = 1, nrow = 2)
```



Comment on the summary statistics and distribution of the ABV variable.

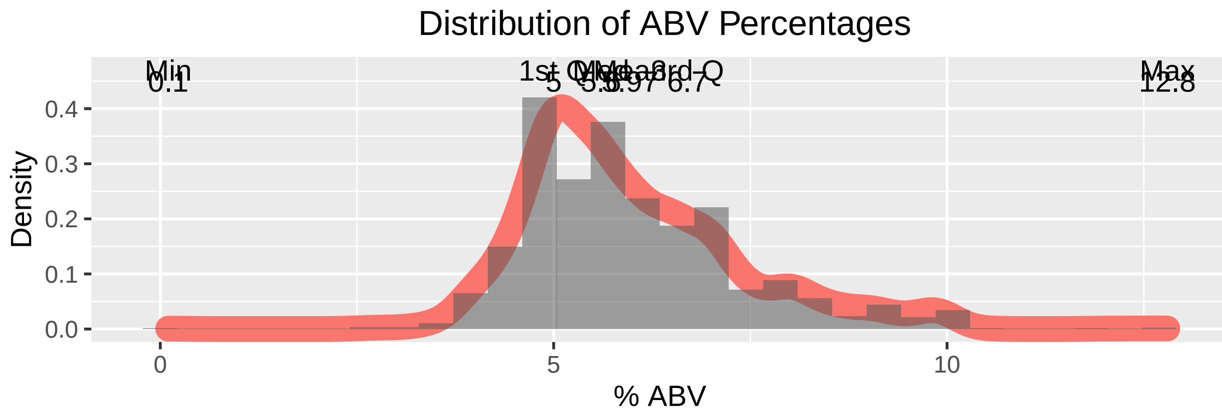
As indicated in the histogram, density and the boxplot, we can observe that there is some amount of right skewness present in the ABV data

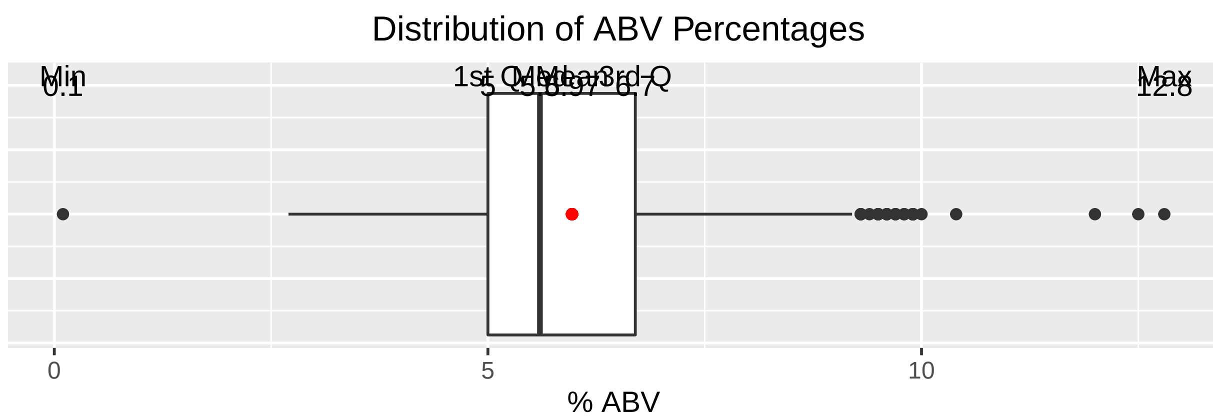
this could be due to the number of outliers present in the dataset. Also the summary stats is present in the output below.

```
#Q6 summary statistics and distribution of ABV
abvsum<-summary(brewerydata$`% ABV`)

#Checked summary with the NA beer removed. Only change is in the minimum. Decided not to remove the dat
noscotty<- brewerydata[!grepl("^606", brewerydata$Beer_ID),]
summary(noscotty$`% ABV`)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   2.700   5.000   5.650   5.977   6.700  12.800
```

```
#get data from the summary
abvsum<-data.frame(table(abvsum))
abvsum$stats[1]<- "Min"
abvsum$stats[2]<- "1st Q"
abvsum$stats[3]<- "Med"
abvsum$stats[4]<- "Mean"
abvsum$stats[5]<- "3rd Q"
abvsum$stats[6]<- "Max"
abvsum<-subset(abvsum, select = -c(Freq))
abvsum$abvsum<-round((as.numeric(as.character(abvsum$abvsum))), digits = 2)
sumstatsstr<-unlist(strsplit(toString(abvsum[1:6,1]), ", "))



abvplotdens<- brewerydata %>% ggplot(aes(x=`% ABV`)) +
  geom_density(aes(color = "red", size = 1)) +
  geom_histogram(aes(y=..density.., alpha = .2)) +
  labs(x = "% ABV", title = " Distribution of ABV Percentages", y = "Density") +
  theme(plot.title = element_text(hjust = .5), legend.position="none") +
  annotate("text", x = c(.1,5, 5.6, 5.97, 6.7, 12.8), y = .45, label = sumstatsstr)+
  annotate("text", x = c(.1,5, 5.6, 5.97, 6.7, 12.8), y = .47, label = abvsum$stats )

abvplotbox<- brewerydata %>% ggplot(aes(x=`% ABV`)) +
  geom_boxplot() +
  labs(x = "% ABV", title = " Distribution of ABV Percentages") +
  theme(plot.title = element_text(hjust = .5), legend.position="none", axis.text.y = element_blank(), a
  annotate("text", x = c(.1,5, 5.6, 5.97, 6.7, 12.8), y = .4, label = sumstatsstr)+
  annotate("text", x = c(.1,5, 5.6, 5.97, 6.7, 12.8), y = .43, label = abvsum$stats)+
  geom_point(aes(x=abvsum$abvsum[4], y=0), colour="red")


ggarrange(abvplotdens, abvplotbox, ncol = 1, nrow = 2)
```





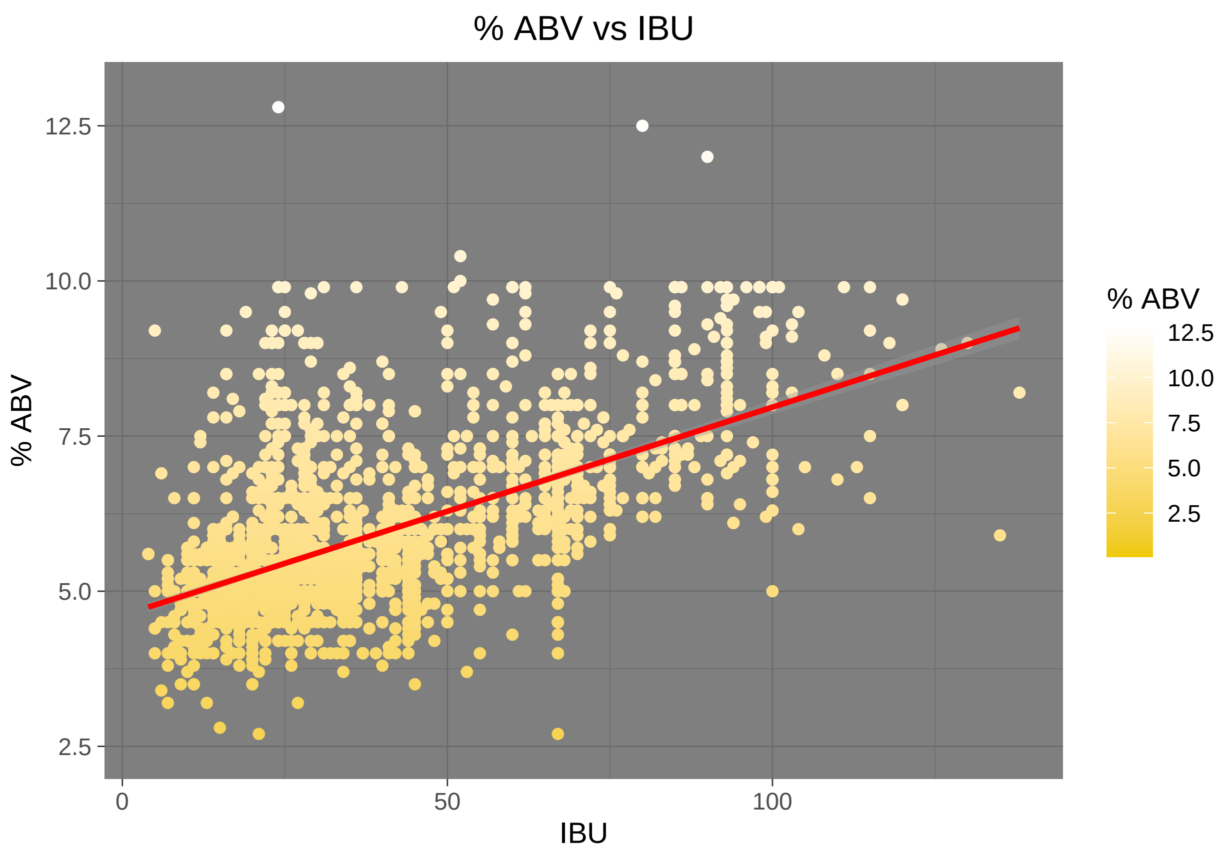
Is there an apparent relationship between the bitterness of the beer and its alcoholic content?

The relationship seems to indicate that generally, breweries are making higher % ABV beers with higher IBU. However, their is no dependency between the two variables since they are obtained through different means. ABV is determined by yeast amount and time to ferment, while IBU is a result of hops added.

```
#Q7 associate IBU and ABV on scatterplot

brewerydata %>% ggplot(aes(x= IBU, y = `% ABV`, color = `% ABV`)) +
  geom_point() +
  ylim(2.5, 13) +
  theme_dark() +
  stat_smooth(method = "lm", color = "red") +
  labs(title = "% ABV vs IBU") +
  theme(plot.title = element_text(hjust = .5)) +
  scale_color_gradient(low = "gold2", high = "white")
```

```
## Warning: Removed 49 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 49 rows containing missing values (geom_point).
```



Prediction Model using KNN

High KNN accuracy for classifying whether a beer is Ale or IPA

```r
#Q8 IBU/ABV for IPA vs any other Ales.
#subset the data to only Styles containing "Ale" and "IPA"
Ale_Data<- brewerydata[grepl("Ale|IPA", brewerydata$Style),]

#modify so we only have 2 levels for the KNN: "IPA" and "Other Ales"
BinaryTest<- Ale_Data
BinaryTest$Style<-ifelse(grepl("IPA", Ale_Data$Style), "IPA", "Other Ales")
BinaryTest$Style<- as.factor(BinaryTest$Style)
BinaryTest<-BinaryTest[, 4:6]

#KNN setup
library(class) #for the knn function
library(caret) #for the confusion matrix function
n.points<-nrow(BinaryTest)
normed1<- (BinaryTest[,1] - min(BinaryTest[,1]))/max(range(BinaryTest[,1]))
normed2<- (BinaryTest[,2] - min(BinaryTest[,2]))/max(range(BinaryTest[,2]))
normed<- data.frame(normed1, normed2)

set.seed(6)
beerloop<-data.frame()
```

```r
for (k in 1:200) {
  predicted.labels <- knn.cv(normed, BinaryTest$Style, k) #predict values
  #how many were right, based on our known values saved above.
  num.correct.labels <- sum(predicted.labels == BinaryTest$Style)
  #correct div by total = accuracy.
  accuracy <- num.correct.labels / n.points
  CM<-confusionMatrix(table(BinaryTest$Style,predicted.labels))
  accuracy <- CM$overall[1]
  #add row to dataframe containing the values from each loop
  beerloop <- rbind(beerloop, data.frame(k, accuracy))
}

#what k has the highest accuracy? answer is 21 with .8964169
which(beerloop$accuracy == max(beerloop$accuracy))
```

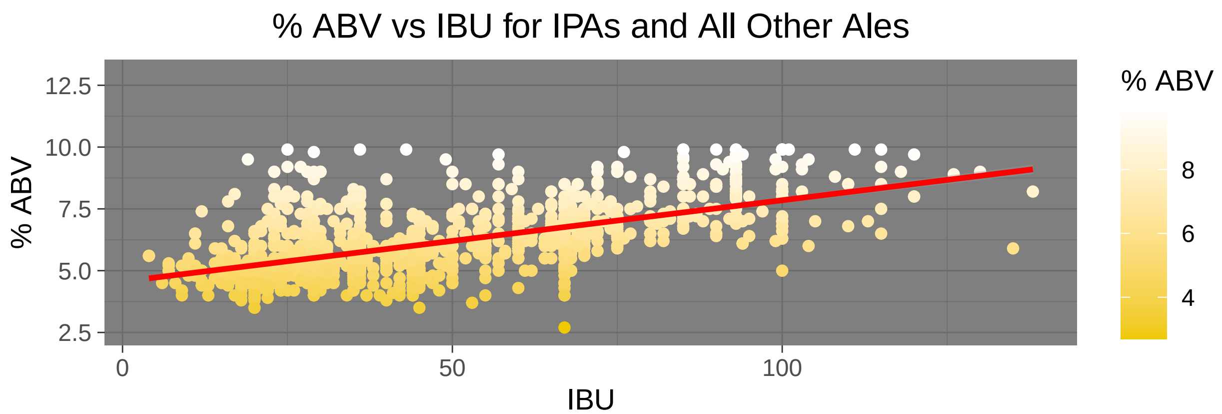
```
## [1] 21
```

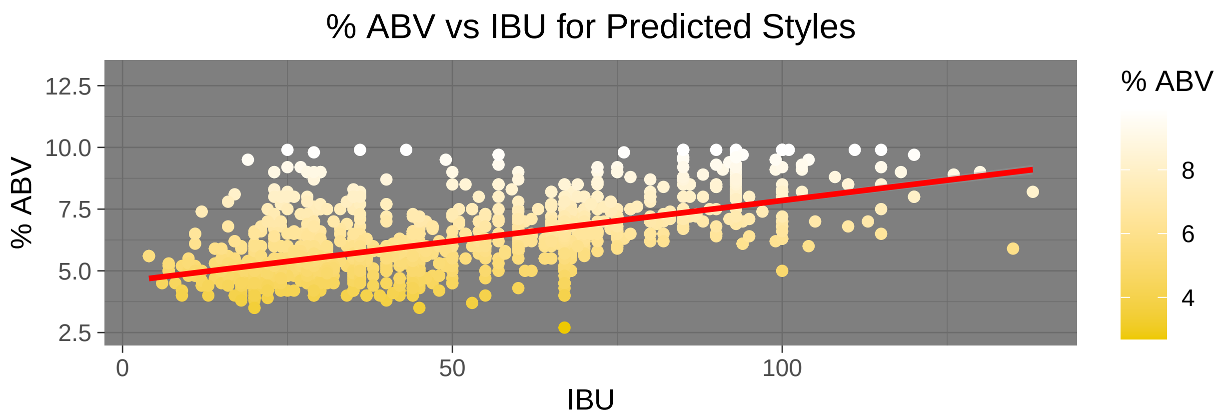
```r
Predictions<-knn.cv(normed, BinaryTest$Style, k = 21)

confusionMatrix(table(BinaryTest$Style, Predictions))
```

```
## Confusion Matrix and Statistics
##
##              Predictions
##               IPA Other Ales
##   IPA         494         77
##   Other Ales   82        882
##
##                Accuracy : 0.8964
##                  95% CI : (0.8801, 0.9112)
##     No Information Rate : 0.6248
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.7787
##
##  Mcnemar's Test P-Value : 0.7511
##
##             Sensitivity : 0.8576
##             Specificity : 0.9197
##          Pos Pred Value : 0.8651
##          Neg Pred Value : 0.9149
##              Prevalence : 0.3752
##          Detection Rate : 0.3218
##    Detection Prevalence : 0.3720
##       Balanced Accuracy : 0.8887
##
##        'Positive' Class : IPA
##
```

```r
# Code for plots
aleabvibuplot<-BinaryTest %>% ggplot(aes(x= IBU, y = `% ABV`, color = `% ABV`)) +
  geom_point() +
  ylim(2.5, 13) +
  theme_dark() +
  stat_smooth(method = "lm", color = "red") +
```

```
  labs(title = "% ABV vs IBU for IPAs and All Other Ales") +
  theme(plot.title = element_text(hjust = .5)) +
  scale_color_gradient(low = "gold2", high = "white")


predicted_style <- knn.cv(BinaryTest[,1:2],BinaryTest$Style,k=21)
BinaryTestKnn <- data.frame(BinaryTest,predicted_style)
BinaryTestKnn <- BinaryTestKnn %>% rename("% ABV" = X..ABV)
BinaryTestKnn <- BinaryTestKnn %>% rename("Predicted Style" = predicted_style)

predaleabvibuplot<- BinaryTestKnn %>% ggplot(aes(x= IBU, y = `% ABV`, color = `% ABV`)) +
  geom_point() +
  ylim(2.5, 13) +
  theme_dark() +
  stat_smooth(method = "lm", color = "red") +
  labs(title = "% ABV vs IBU for Predicted Styles") +
  theme(plot.title = element_text(hjust = .5)) +
  scale_color_gradient(low = "gold2", high = "white")


ggarrange(aleabvibuplot, predaleabvibuplot, ncol = 1, nrow = 2)
```





Is there significant correlation Between % ABV & IBU

```r
# Correlation. There is overwhelming evidence that ABV and IBU are linearly correlated (p-value = <.000

cor.test(brewerydata$`% ABV`,brewerydata$IBU)
```

```
##
##  Pearson's product-moment correlation
##
## data:  brewerydata$`% ABV` and brewerydata$IBU
## t = 36.021, df = 2356, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.5692699 0.6213604
## sample estimates:
##       cor
## 0.5959417
```