caseStudy1

Walter

January 11, 2020

Load Data and Libraries

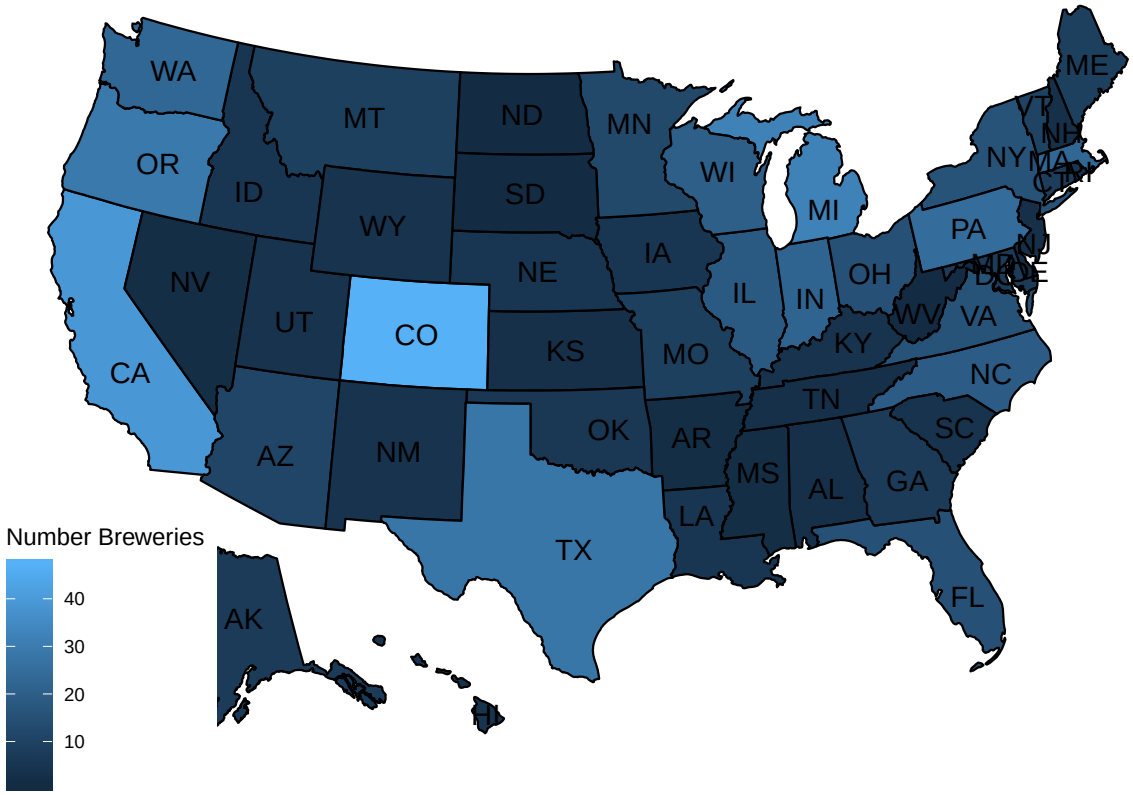
```
beer=read.csv(file.choose())
breweries=read.csv(file.choose())
cities=read.csv(file.choose())
library(dplyr)
library(grid)
library(ggplot2)
library(tidyr)
library(maps)
library(usmap)
library(stringr)
library(class)
library(caret)
library(Hmisc)
library(gridExtra)
library(naniar)
```

2. Merge Beer Data with Brewery Data

```
beerBrew=merge(beer,breweries,by.x="Brewery_id",by.y="Brew_ID")
```

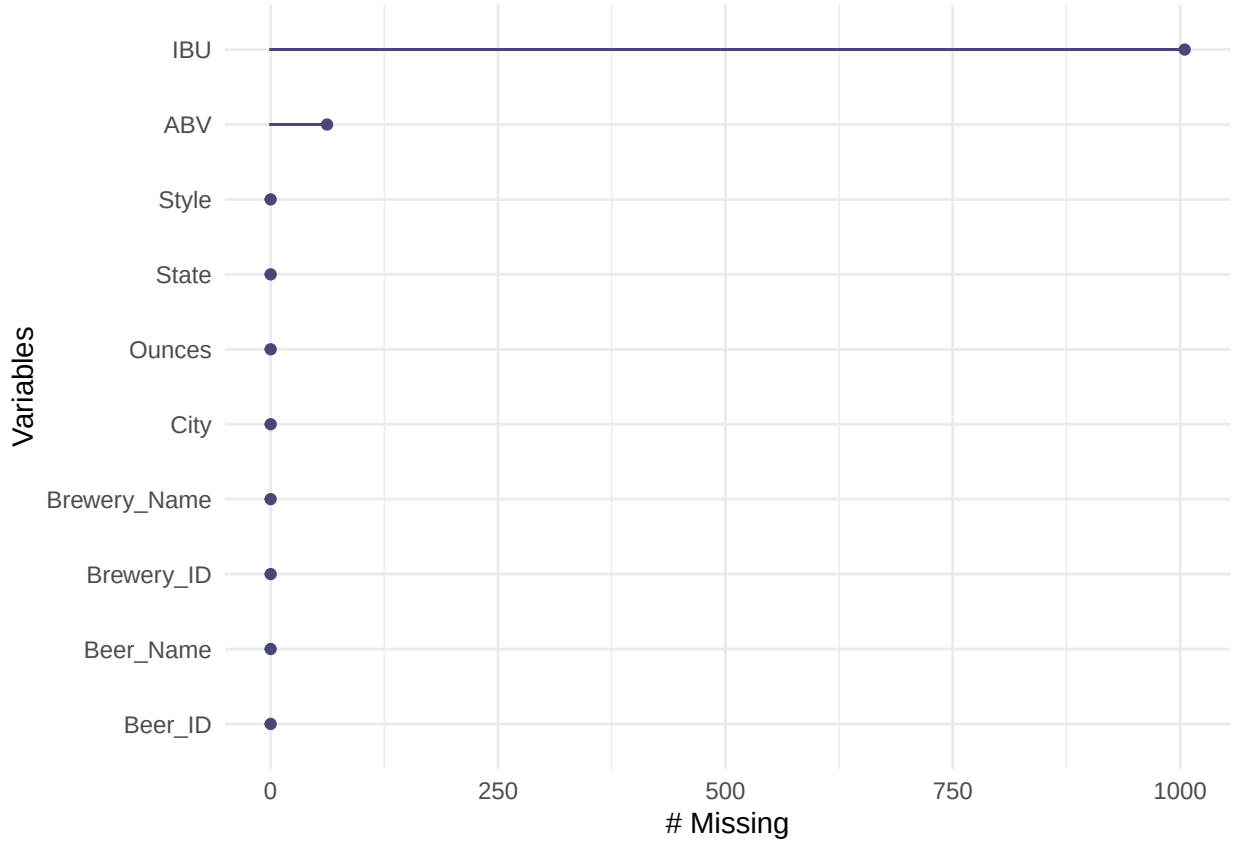
1. Number of Breweries Per State

```
stateCoords=us_map()
# Remove Leading Spaces from State Column of merged Beer Brew Data frame (prepare for join)
# Summarise Each State's Number of Breweries and Beers
stateBrewBeer= beerBrew %>% mutate(State=gsub(" ","",State)) %>% group_by(State) %>% summarise(brews=le

#Join Brewery Beer Data with a dataframe containing state coordinates and population
statePopBrBe = merge(statepop,stateBrewBeer,all.x=TRUE,by.y="State",by.x="abbr")
statePopBrBe=statePopBrBe %>% mutate(brewCap=brews/pop_2015,beerCap=beers/pop_2015)

plot_usmap(data=statePopBrBe,values="brews",labels = TRUE)+scale_fill_continuous(name="Number Breweries
```



3. Address the missing values in each column.

```
# plot missing values in each column, rename some columns
gg_miss_var(beerBrew%>%rename(Beer_Name=Name.x,Brewery_Name=Name.y,Brewery_ID=Brewery_id)
            %>%select(IBU,ABV,Style,State,Ounces,City,Brewery_Name,Beer_Name,
                      Brewery_ID,Beer_ID))
```

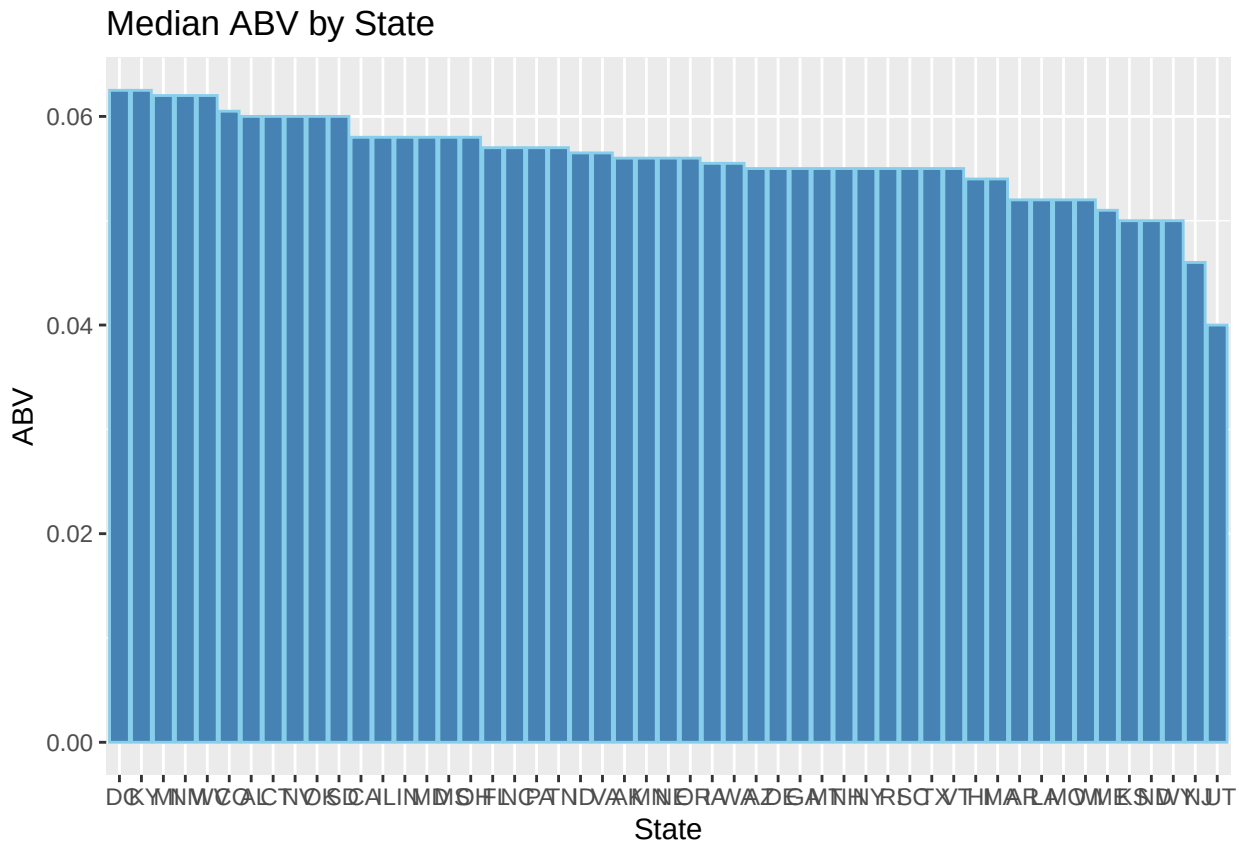



```
# convert empty string Styles to NAs to more easily see missings in all columns
beerBrew$Style[which(beerBrew$Style=="")]=NA
sapply(beerBrew, function(x) sum(is.na(x)))
```

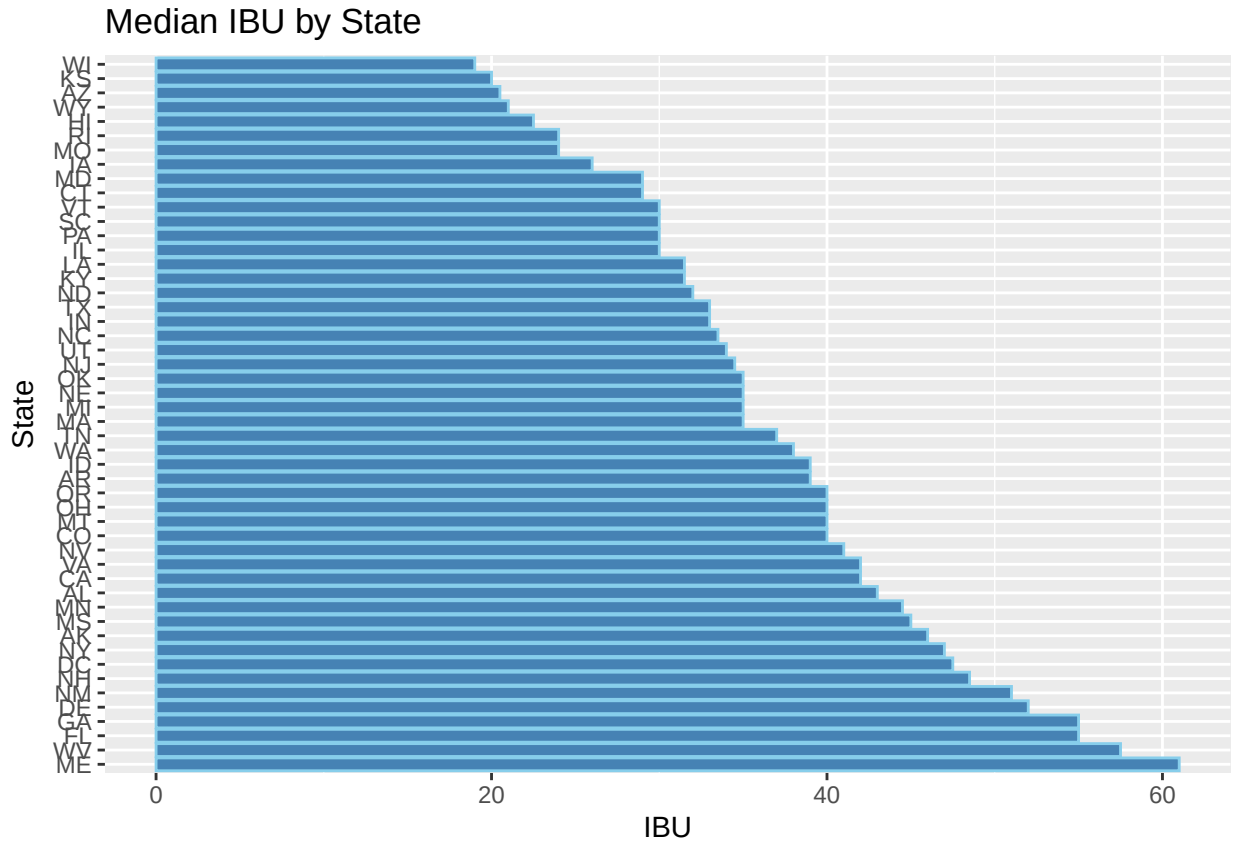
```
## Brewery_id     Name.x    Beer_ID        ABV        IBU      Style     Ounces     Name.y
##          0          0          0         62       1005          5          0          0
##       City      State
##          0          0
```

4.Compute the median alcohol content and international bitterness unit for each state. Plot a bar chart to compare.

```
beerBrew %>% group_by(State) %>%
  filter(!is.na(ABV))%>%
  summarise(ABV=median(ABV)) %>%
   ggplot(aes(x=reorder(State,-ABV),ABV)) +
  geom_bar(stat="identity", position="dodge", color='skyblue',fill='steelblue') +
 # scale_y_continuous(limits = c(0.5,0.07))+
  #coord_flip()+
  xlab("State") +  ylab("ABV") + ggtitle("Median ABV by State")
```




```
beerBrew %>% group_by(State) %>%
 filter(!is.na(IBU))%>%
 summarise(IBU=median(IBU)) %>%
  ggplot(aes(x=reorder(State,-IBU),IBU)) +
 geom_bar(stat="identity", position="dodge", color='skyblue',fill='steelblue') +
 coord_flip()+
 xlab("State") +  ylab("IBU") + ggtitle("Median IBU by State")
```



5. (part 1) Which state has the maximum alcoholic (ABV) beer? Which state has the most bitter (IBU) beer?

```
#find the single most ABV beer
beerBrew %>% filter(!is.na(ABV)) %>% mutate(maxABV=max(ABV)) %>%
  filter(ABV==maxABV) %>%select(State,Name.x,Name.y,ABV)
```

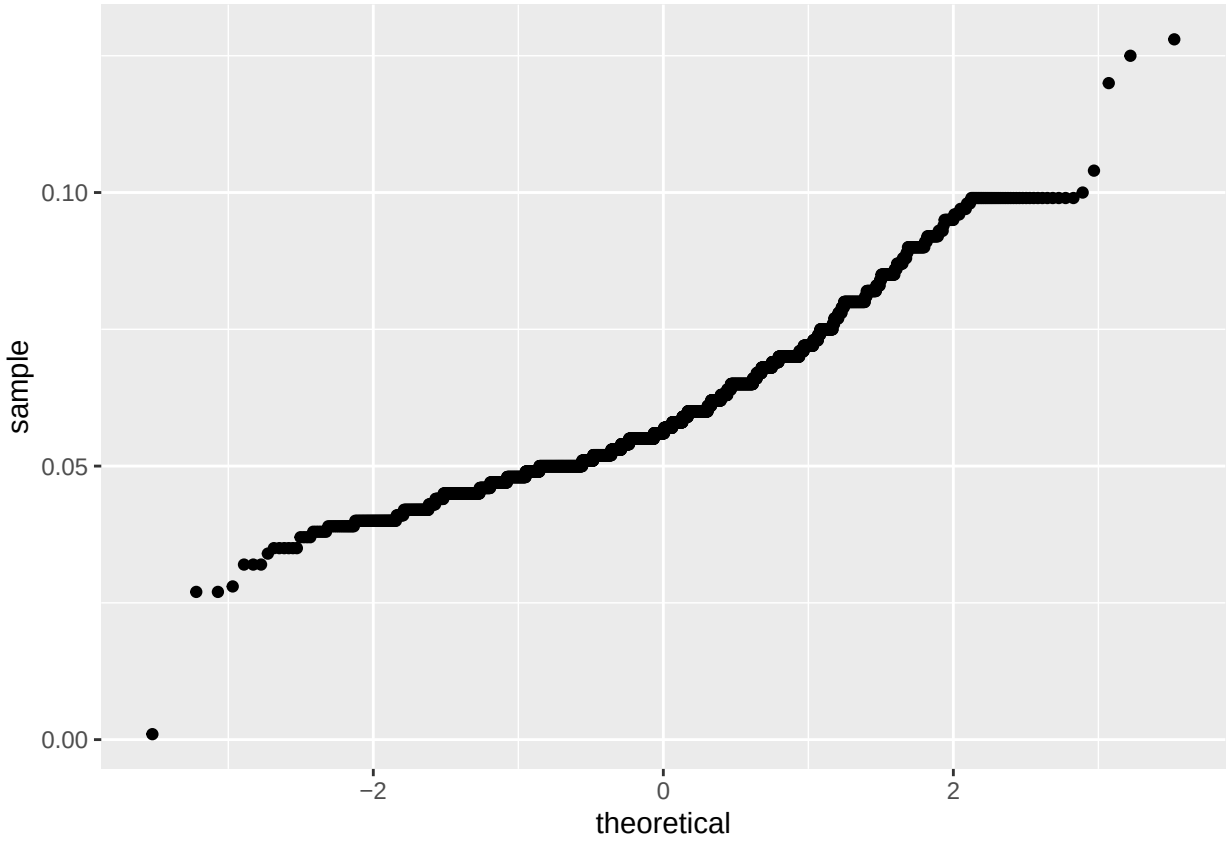
```
##   State                                                Name.x                  Name.y   ABV
## 1    CO Lee Hill Series Vol. 5 - Belgian Style Quadrupel Ale Upslope Brewing Company 0.128
```

```
#
#find the single most bitter beer
beerBrew %>% filter(!is.na(IBU)) %>% mutate(maxIBU=max(IBU)) %>%
  filter(IBU==maxIBU)%>%select(State,Name.x,Name.y,IBU)
```

```
##   State                    Name.x                  Name.y IBU
## 1    OR Bitter Bitch Imperial IPA Astoria Brewing Company 138
```

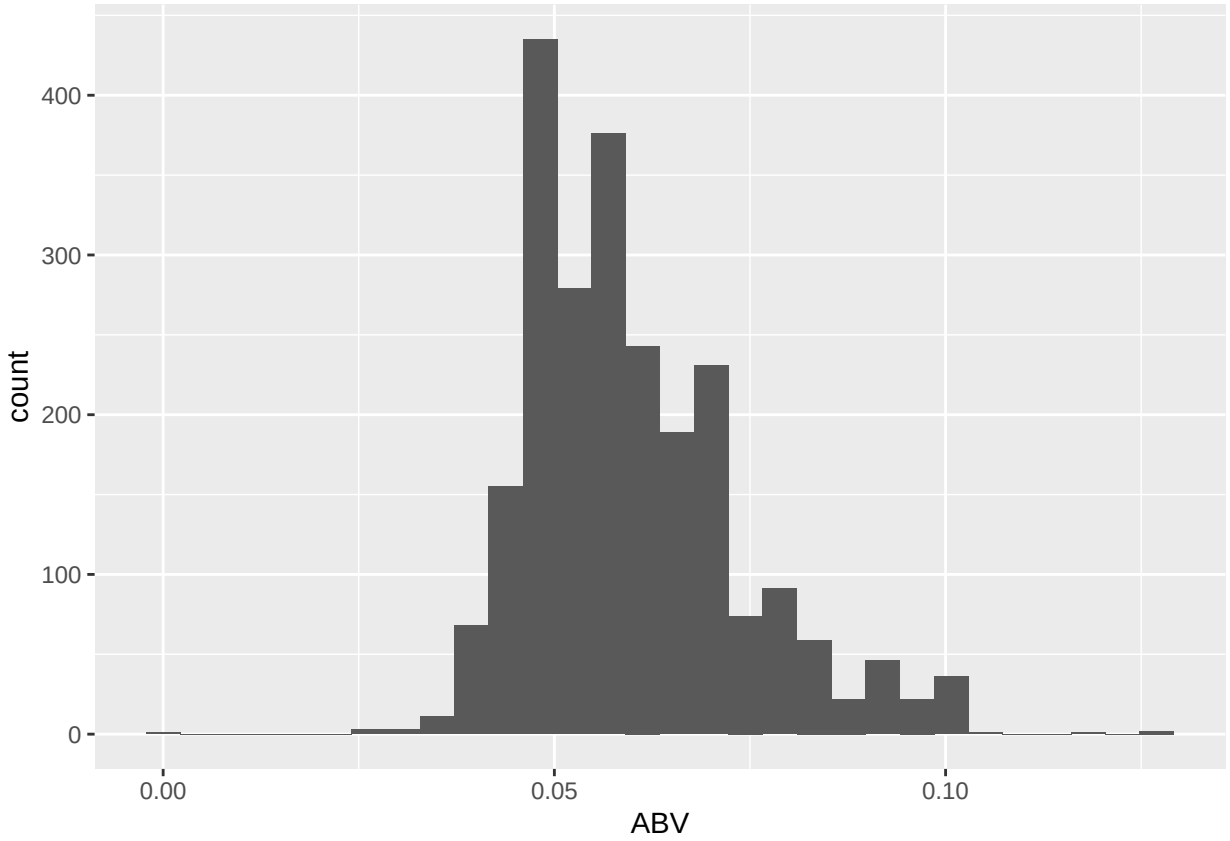
6.Comment on the summary statistics and distribution of the ABV variable The ABV is mostly normally distributed with a noticeable right tail. The mean is Larger than the median.

```
#Check for normality of ABV using qq plot and histogram
beerBrew %>% filter(!is.na(ABV)) %>% ggplot() +stat_qq(aes(sample=ABV))
```




```
beerBrew %>% filter(!is.na(ABV)) %>% ggplot()+geom_histogram(aes(ABV))
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
beerBrew %>% filter(!is.na(ABV)) %>% select(ABV)%>%summary()
```

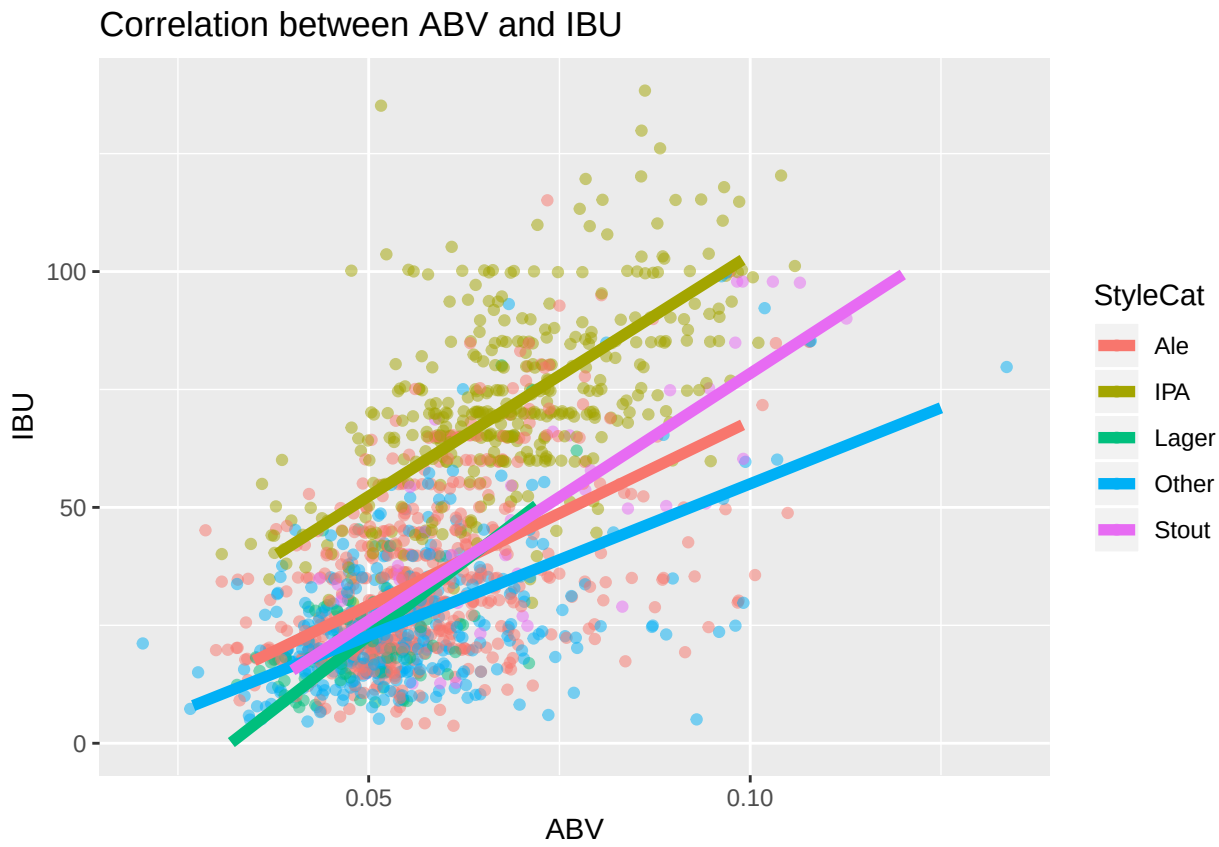
```
##       ABV
##  Min.   :0.00100
##  1st Qu.:0.05000
##  Median :0.05600
##  Mean   :0.05977
##  3rd Qu.:0.06700
##  Max.   :0.12800
```

8. Group beer styles into larger style buckets

```
#Categorize the many styles into 5 groups


  beerBrew$StyleCat= case_when(
    grepl("(India Pale Ale|IPA)",beerBrew$Style) ~ "IPA",
    grepl( "Ale",beerBrew$Style) ~ "Ale",
    grepl("Lager",beerBrew$Style)~"Lager",
    grepl("Stout",beerBrew$Style)~"Stout",
    TRUE~"Other"
  )
```

7. Is there an apparent relationship between the bitterness of the beer and its alcoholic content? Draw a scatter plot. Make your best judgment of a relationship and EXPLAIN your answer. There is a moderate positive correlation between ABV and IBU. The upward slope is evidence of a positive relationship. The points' moderate to small deviations from the trendline is evidence of a moderate to weak relationship.

```
beerBrew %>% filter(!is.na(ABV)&!is.na(IBU))%>%

ggplot(aes(ABV,IBU,color=StyleCat))+geom_point(position=position_jitter(width=0.01),alpha=0.5)+geom_smo
```



We address the feasability of using ABV and IBU to predict a Beer's Style. We are creating a classifier object that will have an input of a list of ABV and IBU values. Its output will be a list of Beer Styles.

Prepare data set for KNN

```
# remove NAs in columns which will use for KNN
beerBrewClean=beerBrew %>% filter(!is.na(ABV)&!is.na(IBU)&!is.na(StyleCat))
```

We randomly divide the dataset of Beers into two parts. One to train the classifier function on. Another to test how well the classifier can classify Beer Styles.
The Sensitivity represents the probability our classifier can classify an Ale when we present it with an Ale's IBU and ABV Values. The Specificity represents the probability our classifier can classify an IPA when we present it with an IPA's IBU and ABV values.

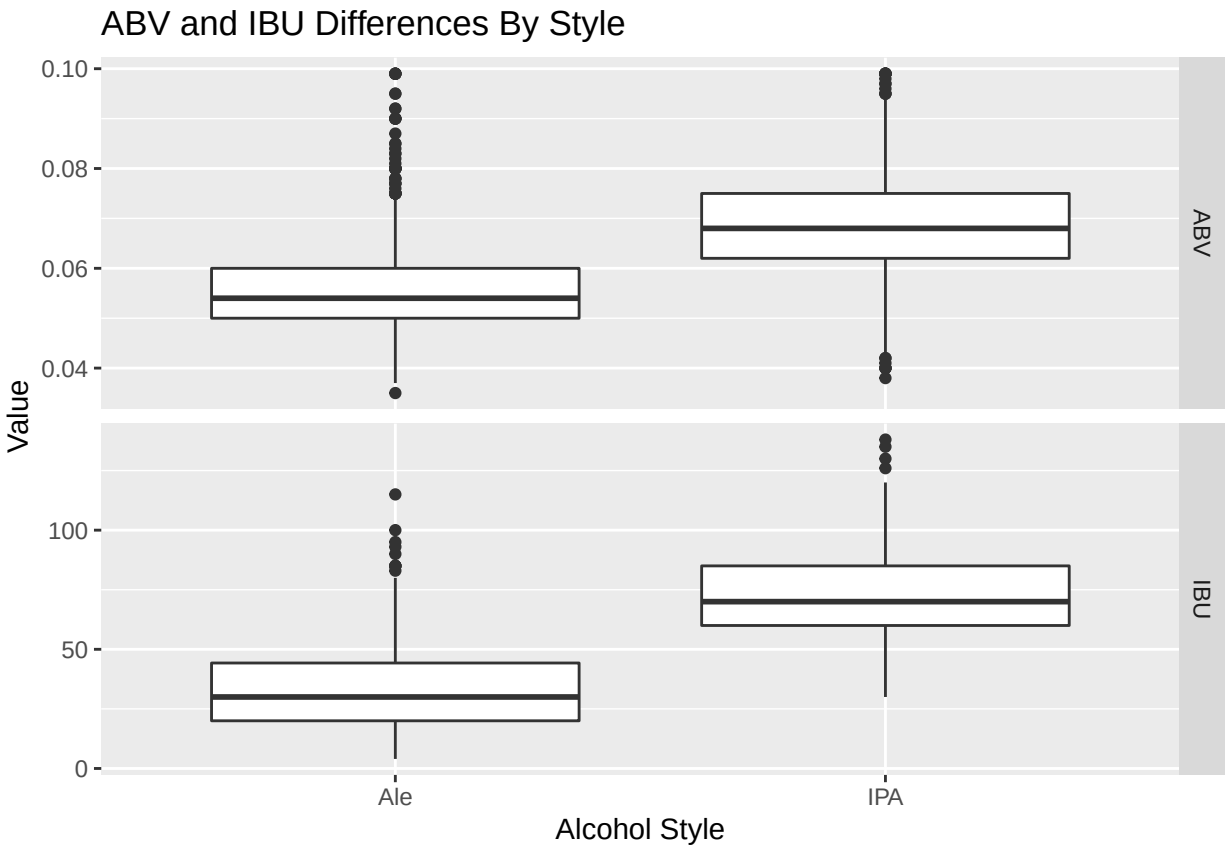
```
# Split percentage of train test
splitPerc=0.7
#Response Variable of KNN
response="StyleCat"
#data is just the merged Beer and Brewery dataframe without NAs and IPA,Ales only
data=beerBrewClean %>% filter(StyleCat %in% c("Ale","IPA"))
#column names of explanatory variables for KNN
explanatory=c("ABV","IBU")
iterations=100
#empty arrays to store Accuracy, Sensitivity and SPecificity of model performance
```

```
#with randomly shuffled train and tests
masterAcc=double(iterations)
masterSens=double(iterations)
masterSpec=double(iterations)


for( x in 1:iterations){
# remove NAs from necessary columns

# scale explanatories
data[,explanatory]=scale(data[,explanatory])

trainIndices = sample(1:dim(data)[1],round(splitPerc * dim(data)[1]))
train = data[trainIndices,]
test = data[-trainIndices,]
classifications=knn(train[,explanatory],test[,explanatory],train[,response],k=3)

  CM = confusionMatrix(table(classifications,test[,response]))
  masterAcc[x] = CM$overall[1]
  masterSens[x]=CM$byClass[1]
  masterSpec[x]=CM$byClass[2]
  }
MeanAcc = mean(masterAcc)
MeanSens=mean(masterSens)
MeanSpec=mean(masterSpec)
```

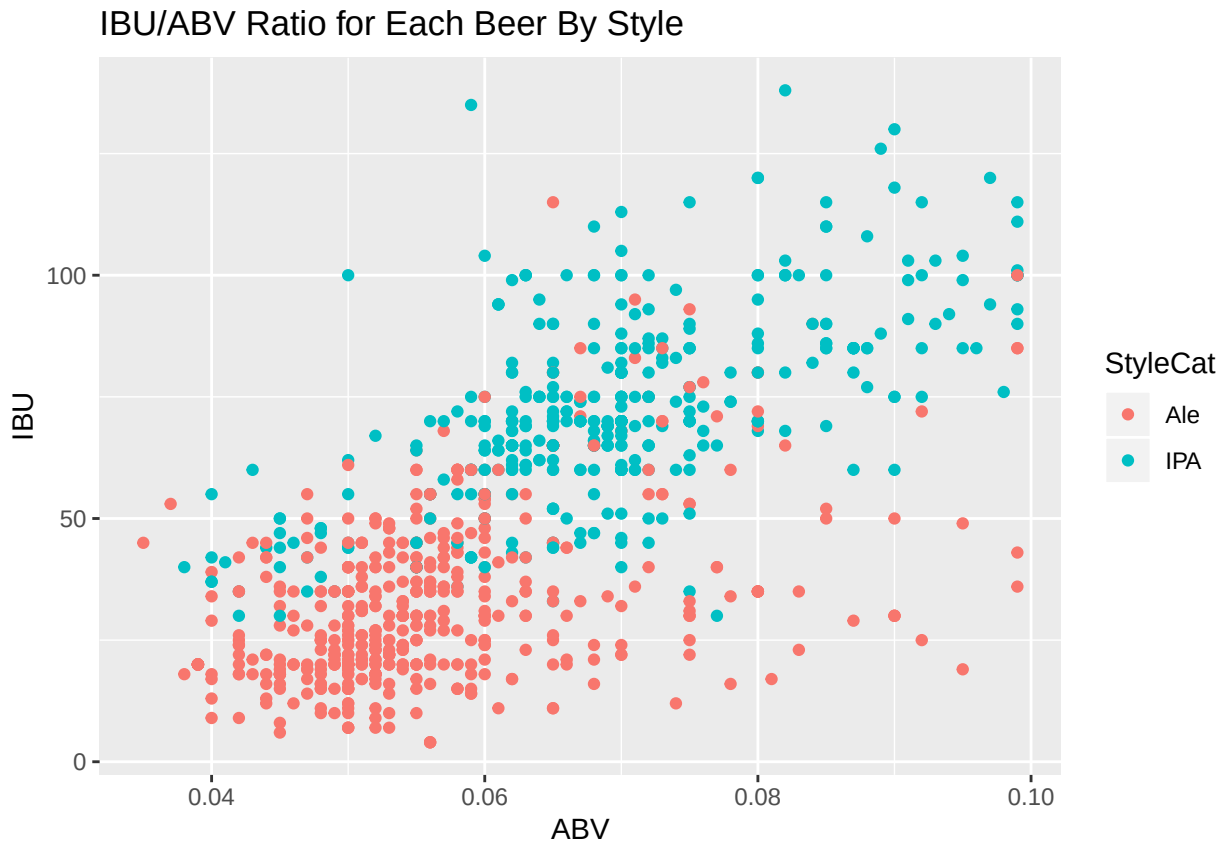
How do Ales and IPAs differ in terms of ABV and IBU? How much more alcoholic or bitter is one style over the other?

Visualize difference in IBU and ABV between Styles

```
beerBrewClean %>% filter(StyleCat %in% c("Ale","IPA")) %>% select(Beer_ID,ABV,IBU,StyleCat)%>%
  gather("Variable","Value",c(-StyleCat,-Beer_ID))%>%
ggplot() + geom_boxplot(aes(StyleCat,Value)) + scale_x_discrete(name="Alcohol Style") +
   labs(title="ABV and IBU Differences By Style") + facet_grid(Variable~.,scales = "free_y")
```



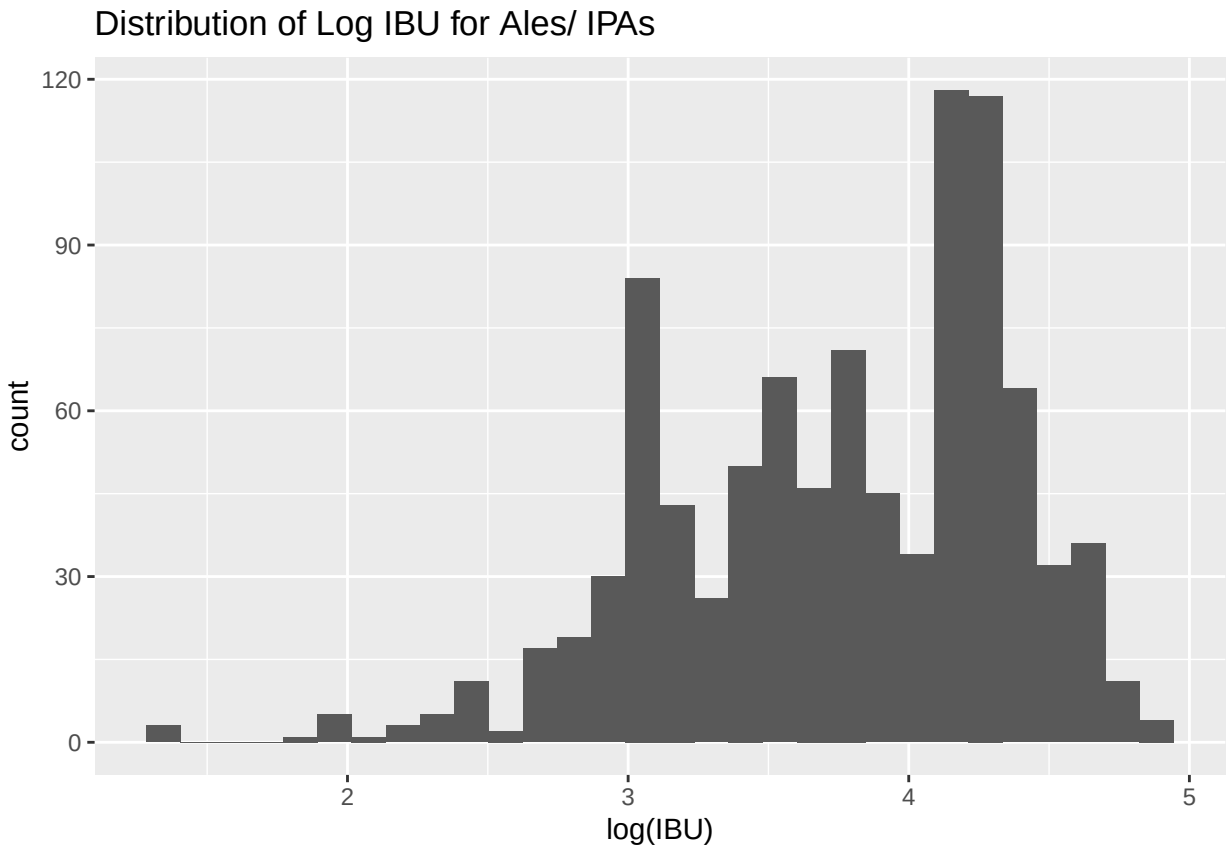

```
beerBrewClean %>% filter(StyleCat %in% c("Ale","IPA")) %>% ggplot(aes(color=StyleCat,ABV,IBU)) +
  geom_point()+labs(title="IBU/ABV Ratio for Each Beer By Style")
```



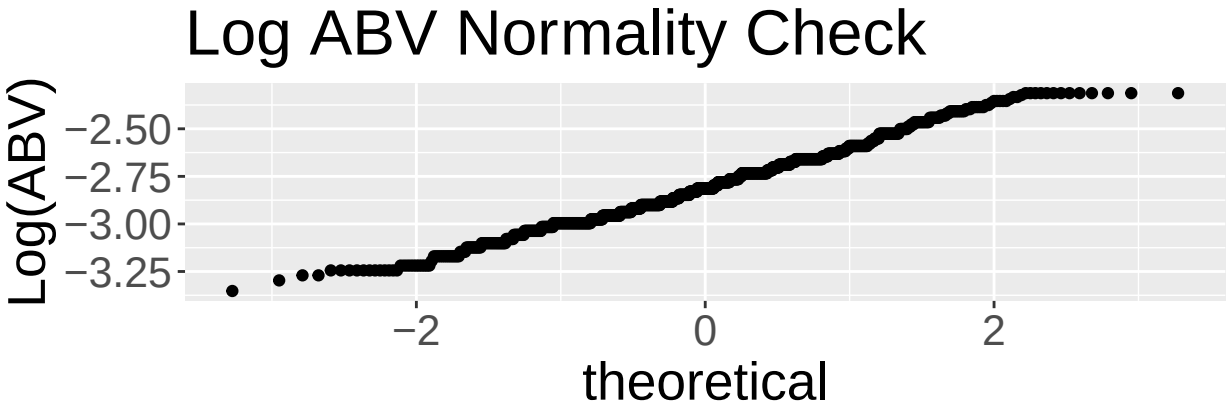
Testing for significant differences in ABV and IBU between IPA and Ales Check the data to see if ABV and IBU form bell curves. Bell Curve Distributions allow us to generalize our conclusions to loarger populations.

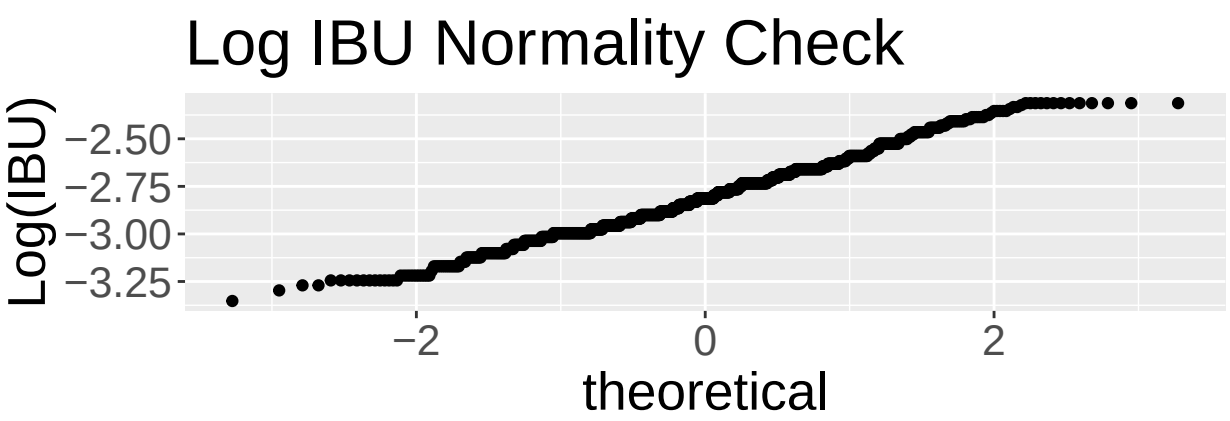
```
# Assumptions  Central Limit Theorem can be invoked
normalityBeer= beerBrewClean %>% filter(StyleCat %in% c("Ale","IPA")) %>% ggplot()
#+ stat_qq(aes(sample=log(ABV)))


qqABV= beerBrewClean %>% filter(StyleCat %in% c("Ale","IPA")) %>% ggplot() +stat_qq(aes(sample=log(ABV))
    theme(text = element_text(size=20))

beerBrewClean %>% filter(StyleCat %in% c("Ale","IPA")) %>% ggplot() + geom_histogram(aes(log(IBU)))+ lab
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
qqIBU=beerBrewClean %>% filter(StyleCat %in% c("Ale","IPA")) %>% ggplot() +
  stat_qq(aes(sample=log(ABV)))+ylab("Log(IBU)")+labs(title="Log IBU Normality Check")+
    theme(text = element_text(size=20))

qqABV=ggplot_gtable(ggplot_build(qqABV))
qqIBU=ggplot_gtable(ggplot_build(qqIBU))
maxWidth = unit.pmax(qqABV$heights[2:3], qqIBU$heights[2:3])

qqABV$heights[2:3] <- maxWidth
qqIBU$heights[2:3] <- maxWidth

grid.arrange(qqABV, qqIBU, heights = c(2, 2))
```






```
beerBrewClean %>%  group_by(StyleCat) %>% summarise(sd=sd(ABV),sdIBU=sd(IBU))
```

```
## # A tibble: 5 x 3
##   StyleCat      sd sdIBU
##   <chr>      <dbl> <dbl>
## 1 Ale      0.0111   18.0
## 2 IPA      0.0122   19.5
## 3 Lager    0.00711  13.4
## 4 Other    0.0130   15.9
## 5 Stout    0.0186   24.1
```

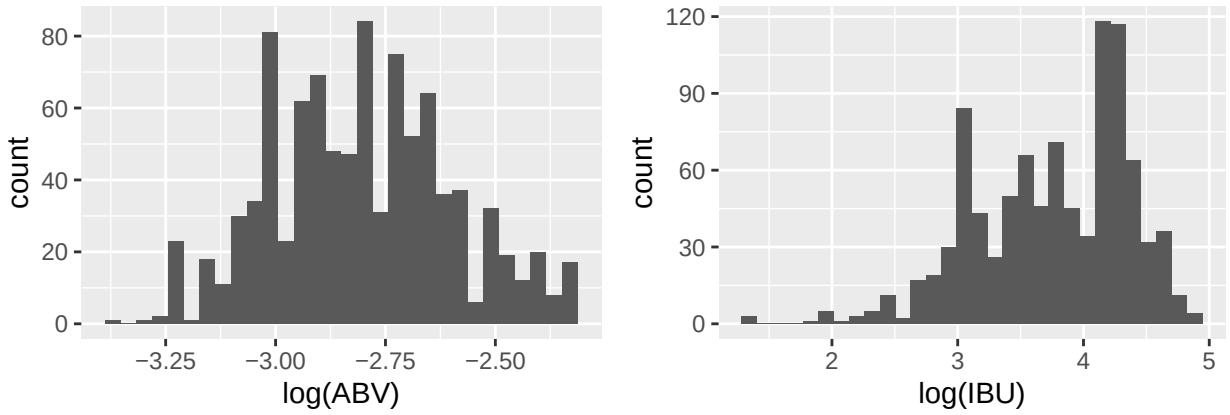
```
histABV= normalityBeer + geom_histogram(aes(log(ABV)))
histIBU=normalityBeer + geom_histogram(aes(log(IBU)))
histABV=ggplot_gtable(ggplot_build(histABV))
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
histIBU=ggplot_gtable(ggplot_build(histIBU))
```

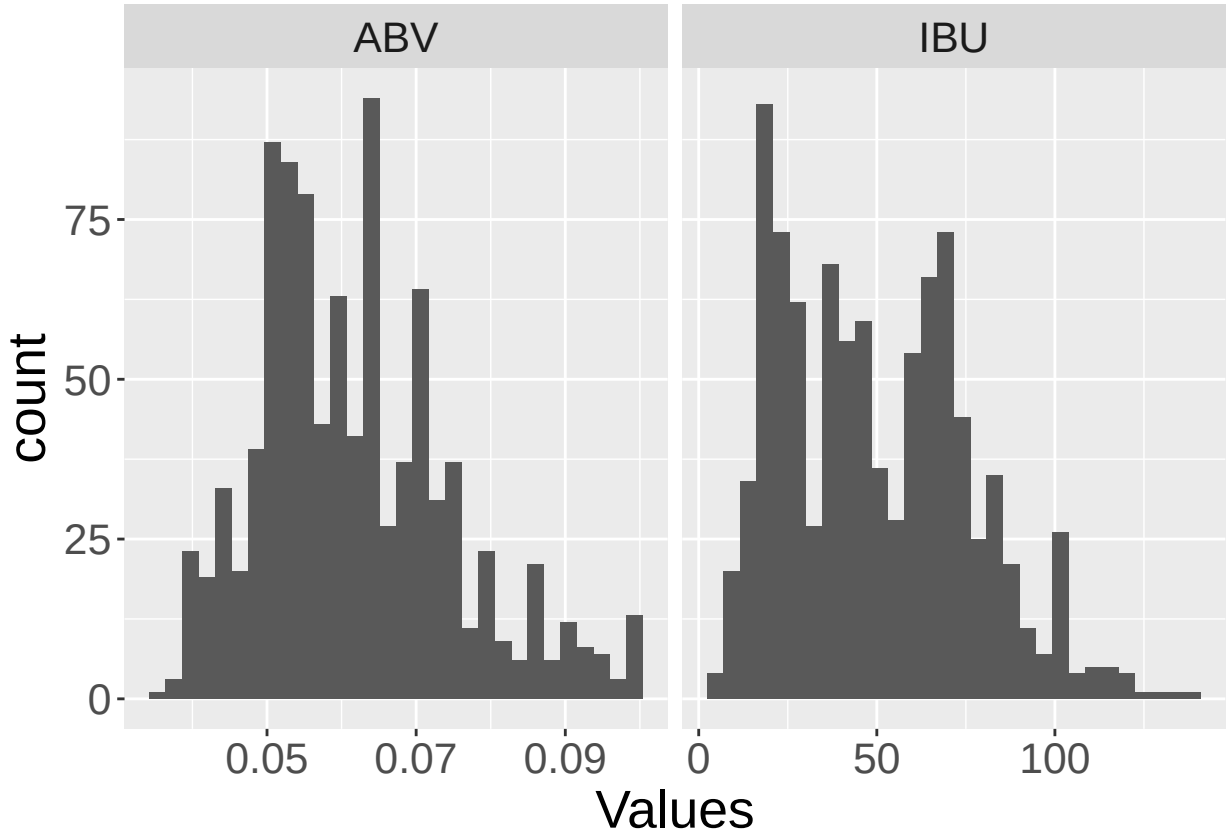
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
maxWidth = unit.pmax(histABV$heights[2:3], histIBU$heights[2:3])

histABV$heights[2:3] <- maxWidth
histIBU$heights[2:3] <- maxWidth

grid.arrange(histABV, histIBU, heights = c(2, 2),ncol=2)
```




```
beerBrewClean %>% filter(StyleCat %in% c("Ale","IPA")) %>%
  select(Beer_ID,ABV,IBU)%>%
gather( "Variable", "Values", -Beer_ID)%>%
  ggplot() + geom_histogram(aes(Values)) + facet_grid(~Variable,scales = "free_x") +
    theme(text = element_text(size=20))
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
ABUtest=t.test(log(ABV)~StyleCat,var.equal=TRUE,beerBrewClean %>% filter(StyleCat %in% c("Ale","IPA") &

ibuTest=t.test(log(IBU)~StyleCat,var.equal=TRUE,beerBrewClean %>% filter(StyleCat %in% c("Ale","IPA") &
```

In terms of ABV, median of IPA compared to median of Ales is a ratio ranging between

```
exp(ABUtest$conf.int)
```

```
## [1] 0.7976278 0.8361243
## attr(,"conf.level")
## [1] 0.95
```

In terms of IBU, median of IPA compared to median of Ales is a ratio ranging between

```
exp(ibuTest$conf.int)
```

```
## [1] 0.4079911 0.4585913
## attr(,"conf.level")
## [1] 0.95
```

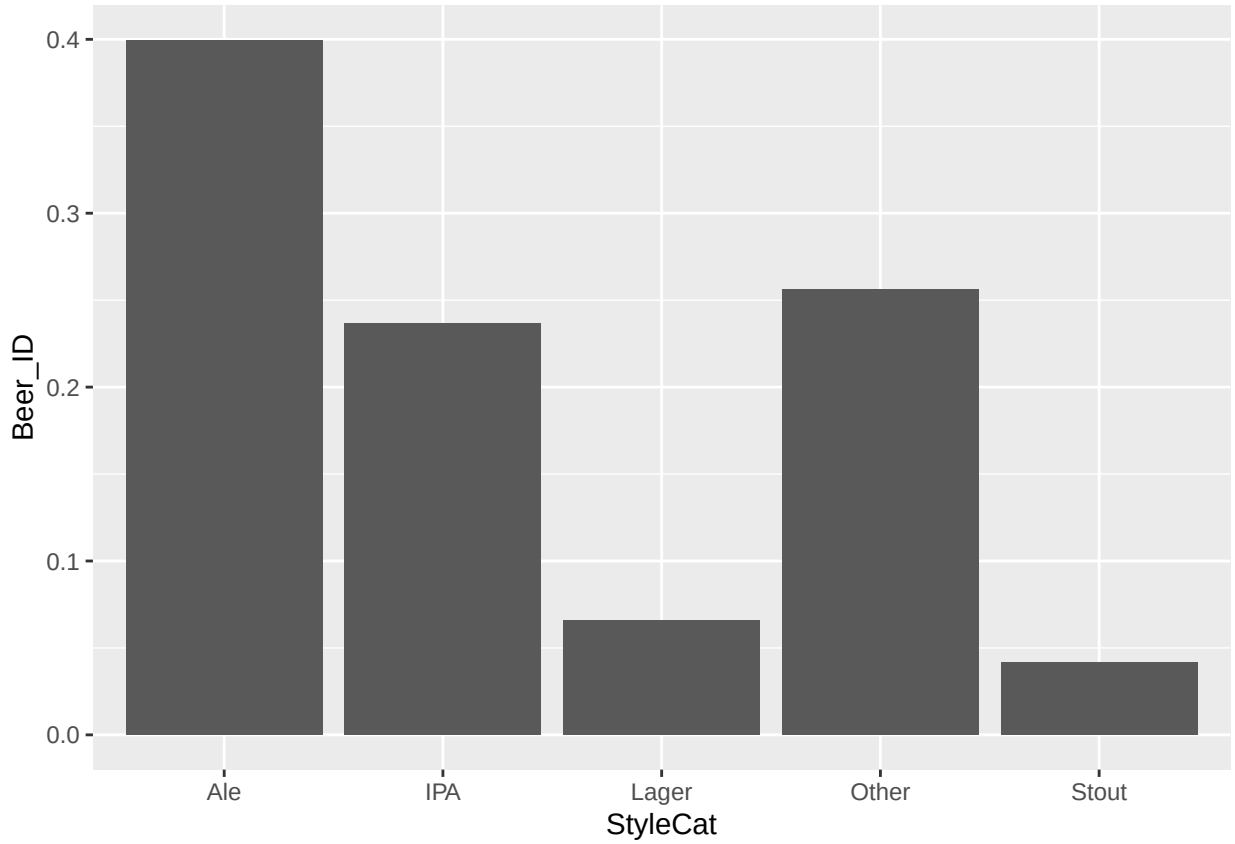
Test set is the records of missing IBUs Train set is the records that have IBU not missing

Identifying the missing Styles in underserved cities

1.Find the national percentages of each Style Category visually

```
#national percentage of styles
beerBrew %>% ggplot() + stat_summary(geom="bar",aes(StyleCat,Beer_ID),fun.y=function(x){
```

```
  length(unique(x))/length(unique(beerBrew$Beer_ID))
})
```



2. Table Format of national percentages

```
nationalPct=beerBrew %>% group_by(StyleCat) %>% summarise(pct=n()/with(beerBrew,length(unique(Beer_ID))))
```

3. CityData contains the population of 314 of AMerica's Most populous cities.
   Add a column that contains the population of the city for each Beer's Brewery.

```
#remove the leading space in all States of beerBrew
beerBrew$State = with(beerBrew, gsub(as.character(State),pattern=" ",replacement = ""))
beerBrew$City=as.character(beerBrew$City)
cities$City= with(cities,as.character(City))
cities$State=with(cities,as.character(State))

#change State abbreviation to full name
States=map_data("state")
lookup = data.frame(abb = state.abb, State = state.name)
lookup$abb=as.character(lookup$abb)
lookup$State=as.character(lookup$State)
lookup=rbind(lookup,c("DC","district of columbia"))
# turn abbreviations to state names for beerBrew because cities has full names
beerBrew=merge(beerBrew,lookup,all.x=TRUE,by.x="State",by.y="abb")

#remove leading blanks in cities State field
cities$State = str_remove(cities$State,"^\\s")
```

```
# FINALLY
beerBrewCities = left_join(beerBrew, cities, by=c("City"="City","State.y"="State"))
```

convert population data string to number

```
beerBrewCities$X2018 = with(beerBrewCities,as.numeric(str_replace(as.character(X2018),",","")))
```

```
## Warning in eval(substitute(expr), data, enclos = parent.frame()): NAs introduced by coercion
```

```
beerBrewCities$X2010 = with(beerBrewCities,as.numeric(str_replace(as.character(X2010),",","")))
```

```
## Warning in eval(substitute(expr), data, enclos = parent.frame()): NAs introduced by coercion
```

```
#write.csv( beerBrewCities %>% arrange(desc(X2018)) %>% head(),"BeerLeftCityState.csv" )
```

Which cities have percentages of Style that are less than the national average's percentage?

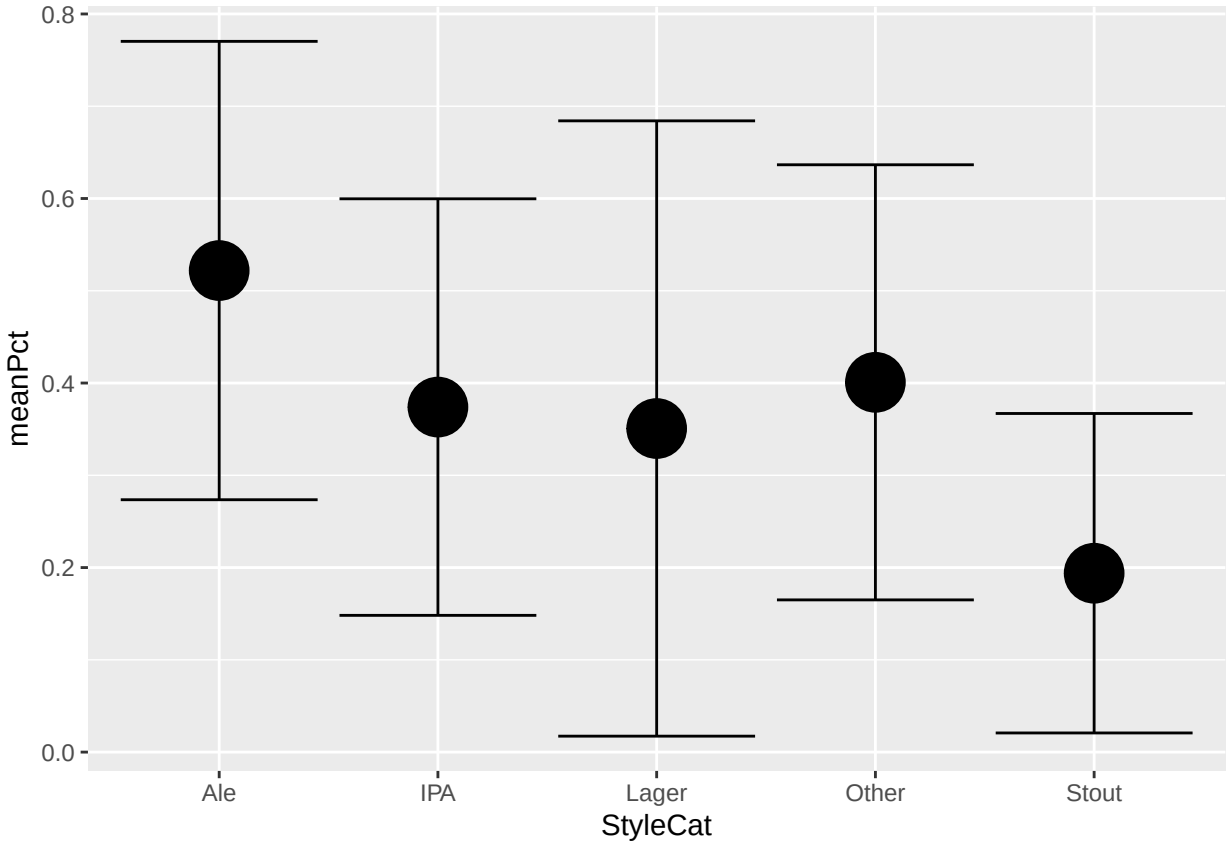
3. For the top 314 most populous cities, find the average percentage of each style and the standard deviation of the percentage of each style.

```
  stylePctByState=beerBrew %>% group_by(State,City) %>%
  #find the total number of beers for each city without aggregating
  mutate(nBeers=length(unique(Beer_ID))) %>%
  ungroup()%>%
  #find the total number of beers for each city,style combination
  group_by(State,City,StyleCat) %>% summarise(nBeersPerStylePerCity=
                                                length(unique(Beer_ID)),nBeers=
                                              mean(nBeers)) %>%
  #divide the number of Lagers in Minneapolis by the number of beers in minneapolis
  mutate(stylePct=nBeersPerStylePerCity/nBeers)%>% arrange(desc(stylePct)) %>%
  ungroup()%>%
  #find the average and standard deviation of all the cities' percentages of Lager,Ale,etc.
  group_by(StyleCat) %>%
  summarise(meanPct=mean(stylePct),sdPct=sd(stylePct))
stylePctByState
```

```
## # A tibble: 5 x 3
##   StyleCat meanPct sdPct
##   <chr>      <dbl> <dbl>
## 1 Ale        0.522 0.248
## 2 IPA        0.374 0.226
## 3 Lager      0.351 0.333
## 4 Other      0.401 0.236
## 5 Stout      0.194 0.173
```

4. What are the national percentages and the variation of each style's percentage by city?

```
stylePctByState %>% ggplot() + geom_point(aes(StyleCat,meanPct),size=10)+geom_errorbar(aes(
  x=StyleCat,ymin= meanPct-sdPct,ymax=meanPct+sdPct
))
```



In order to compare each city's style percentage to the national percentage for each style. We need to find the percentage of each style in each city.

```
targetCities = beerBrewCities %>% group_by(State,City) %>%
  #find the number of breweries per capita to be used as measure of underserved cities
  mutate(brewPcap=length(unique(Brewery_id))/
                                                    mean(X2018),nBeers=length(unique(Beer_ID)),X2018=mean
  #find the number of beers in each city and the population in each city
  #arrange(desc(brewPcap)) %>%
  ungroup() %>%
  #find the number of beers for each particulr style in each city
  group_by(State,City,StyleCat) %>% summarise(nBeersPerStylePerCity=
                                                 length(unique(Beer_ID)),nBeers=
                                            mean(nBeers),brewPcap=mean(brewPcap),X2018=mean(X2018)) %>%
  mutate(stylePct=nBeersPerStylePerCity/nBeers) #%>% ungroup() %>%
  #top_n(10,brewPcap)
head(targetCities,10)
```

```
## # A tibble: 10 x 8
## # Groups:   State, City [4]
##    State City      StyleCat nBeersPerStylePerCity nBeers   brewPcap  X2018 stylePct
##    <chr> <chr>     <chr>                    <int>  <dbl>      <dbl>  <dbl>    <dbl>
##  1 AK    Anchorage Ale                          7     15  0.0000137 291538    0.467
##  2 AK    Anchorage IPA                          5     15  0.0000137 291538    0.333
##  3 AK    Anchorage Other                        3     15  0.0000137 291538    0.2
##  4 AK    Juneau    Ale                          1      2 NA             NA    0.5
##  5 AK    Juneau    Other                        1      2 NA             NA    0.5
```

```
##  6 AK    Soldotna  Ale                          3      4 NA             NA    0.75
##  7 AK    Soldotna  IPA                          1      4 NA             NA    0.25
##  8 AK    Talkeetna Ale                          2      4 NA             NA    0.5
##  9 AK    Talkeetna IPA                          1      4 NA             NA    0.25
## 10 AK    Talkeetna Stout                        1      4 NA             NA    0.25
```

Cities that are missing a style do not have observations for that style. Add observations containing 0% for cities that have no beers for a certain style.

```
#create a subset of the cities and style percentages data to test a function
# that will add observations containing 0% for cities that ar emissing styles
small = targetCities %>% ungroup() %>% top_n(10,brewPcap)



#juust right join the greenbay
small= small[small$City=="Green Bay",]
missingStyle0 =  function(small,a)
  {
  #right join the complete list of styles to each city's data to create NAs for
  #missing styles
  smallCat= small %>% merge(stylePctByState,all.y=TRUE)
  # find the rows that are missing and put 0% for the style percentage
  naIndices=which(is.na(smallCat$City))
  smallCat$stylePct[naIndices]=0
  # for the rest of the rows, copy the information from the non-NA rows
  smallCat$State[naIndices]=max(smallCat$State[-naIndices])
  smallCat$City[naIndices]=max(smallCat$City[-naIndices])
  smallCat$brewPcap[naIndices]=max(smallCat$brewPcap[-naIndices])
  smallCat$X2018[naIndices]=max(smallCat$X2018[-naIndices])
  return(smallCat)
}
missingStyle0(small)
```

```
##   StyleCat State      City nBeersPerStylePerCity nBeers     brewPcap  X2018 stylePct   meanPct
## 1      Ale    WI Green Bay                     1      2 1.906959e-05 104879      0.5 0.5219114
## 2      IPA    WI Green Bay                     1      2 1.906959e-05 104879      0.5 0.3739356
## 3    Lager    WI Green Bay                    NA     NA 1.906959e-05 104879      0.0 0.3507032
## 4    Other    WI Green Bay                    NA     NA 1.906959e-05 104879      0.0 0.4007520
## 5    Stout    WI Green Bay                    NA     NA 1.906959e-05 104879      0.0 0.1938534
##       sdPct
## 1 0.2484043
## 2 0.2257477
## 3 0.3334354
## 4 0.2357859
## 5 0.1731264
```

```
test=targetCities %>% ungroup() %>% top_n(10,brewPcap)
# apply this function tothe test dataframe, check to see if missing styles has 0s as style%
test %>% group_by(State,City) %>% do(missingStyle0(.,1))
```

```
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA

## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA

## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
```

```
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf

## # A tibble: 15 x 10
## # Groups:   State, City [3]
##    StyleCat State City      nBeersPerStylePerCity nBeers  brewPcap  X2018 stylePct meanPct sdPct
##    <chr>    <chr> <chr>                     <int>  <dbl>     <dbl>  <dbl>    <dbl>   <dbl> <dbl>
##  1 Ale      CA    Temecula                      2      5 0.0000174 114742   0.4      0.522 0.248
##  2 IPA      CA    Temecula                      1      5 0.0000174 114742   0.2      0.374 0.226
##  3 Lager    CA    Temecula                     NA     NA 0.0000174 114742   0        0.351 0.333
##  4 Other    CA    Temecula                      2      5 0.0000174 114742   0.4      0.401 0.236
##  5 Stout    CA    Temecula                     NA     NA 0.0000174 114742   0        0.194 0.173
##  6 Ale      CO    Boulder                      17     41 0.0000838 107353   0.415    0.522 0.248
##  7 IPA      CO    Boulder                       8     41 0.0000838 107353   0.195    0.374 0.226
##  8 Lager    CO    Boulder                       2     41 0.0000838 107353   0.0488   0.351 0.333
##  9 Other    CO    Boulder                      11     41 0.0000838 107353   0.268    0.401 0.236
## 10 Stout    CO    Boulder                       3     41 0.0000838 107353   0.0732   0.194 0.173
## 11 Ale      WI    Green Bay                     1      2 0.0000191 104879   0.5      0.522 0.248
## 12 IPA      WI    Green Bay                     1      2 0.0000191 104879   0.5      0.374 0.226
## 13 Lager    WI    Green Bay                    NA     NA 0.0000191 104879   0        0.351 0.333
## 14 Other    WI    Green Bay                    NA     NA 0.0000191 104879   0        0.401 0.236
## 15 Stout    WI    Green Bay                    NA     NA 0.0000191 104879   0        0.194 0.173
```

```
# all other NAs will match the previous column data
```

For states with missing styleCats add rows with the missing style and 0% as the style percent

```
targets0= targetCities %>% group_by(State,City) %>% do(missingStyle0(.,1))
```

```
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA

## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA

## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf

## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf

## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA

## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA

## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf

## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf

## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA

## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA

## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf

## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf

## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA

## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA

## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf

## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf

## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA

## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA

## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
```

```
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
```

```
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$State[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$City[-naIndices]): no non-missing arguments, returning NA
## Warning in max(smallCat$brewPcap[-naIndices]): no non-missing arguments to max; returning -Inf
## Warning in max(smallCat$X2018[-naIndices]): no non-missing arguments to max; returning -Inf
```

```
#check all cities have 5 styles regardless of if they made any beer with that style
with(targetCities,length(unique(City)))*5
```

```
## [1] 1920
```

```
head(targets0)
```

```
## # A tibble: 6 x 10
## # Groups:   State, City [2]
##   StyleCat State City      nBeersPerStylePerCity nBeers   brewPcap  X2018 stylePct meanPct sdPct
##   <chr>     <chr> <chr>                     <int>  <dbl>      <dbl>  <dbl>    <dbl>   <dbl> <dbl>
## 1 Ale       AK    Anchorage                     7     15  0.0000137 291538    0.467   0.522 0.248
## 2 IPA       AK    Anchorage                     5     15  0.0000137 291538    0.333   0.374 0.226
## 3 Lager     AK    Anchorage                    NA     NA  0.0000137 291538    0       0.351 0.333
## 4 Other     AK    Anchorage                     3     15  0.0000137 291538    0.2     0.401 0.236
## 5 Stout     AK    Anchorage                    NA     NA  0.0000137 291538    0       0.194 0.173
## 6 Ale       AK    Juneau                        1      2 NA                NA    0.5     0.522 0.248
```

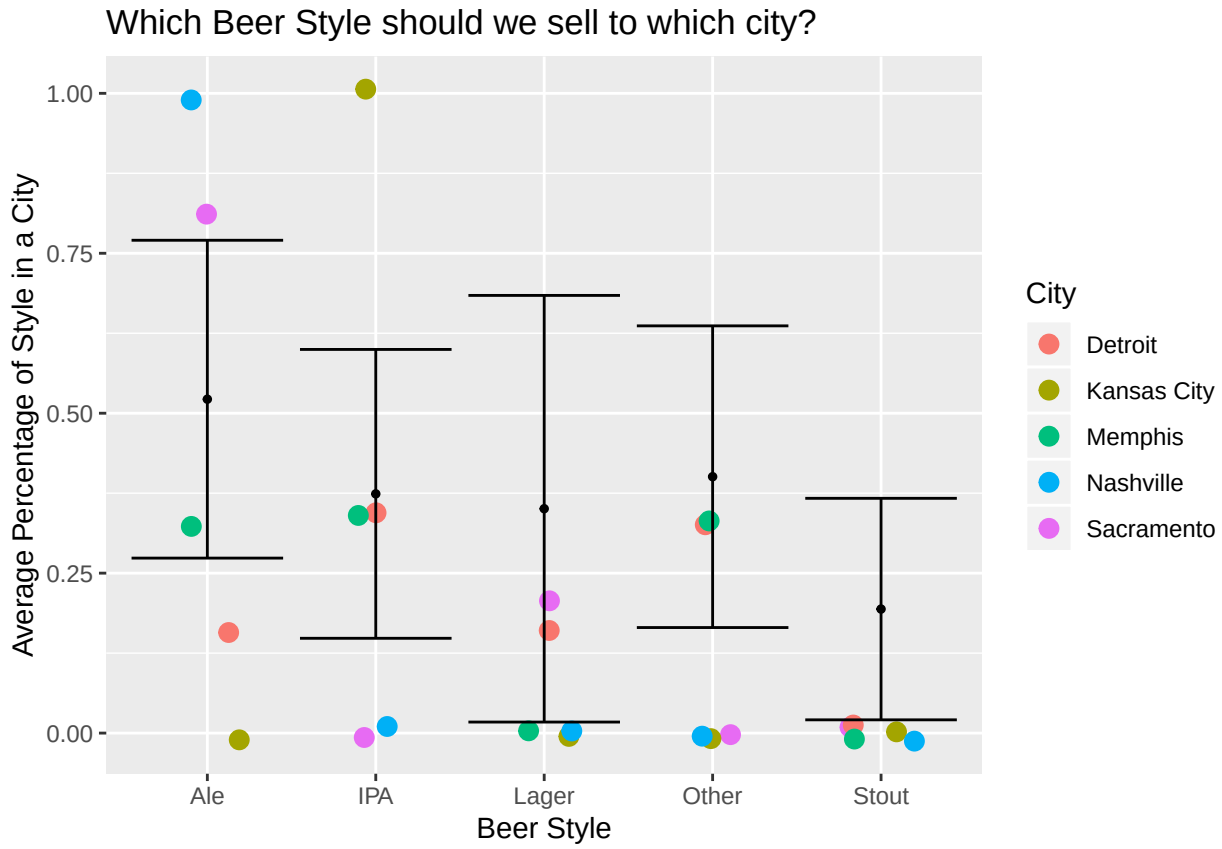
Find the underserved cities which are defined as cities with the lowest breweries per capita.

```
filterCity=targets0 %>%
  ungroup()%>%
  top_n(-25,brewPcap)
filterCity
```

```
## # A tibble: 25 x 10
##    StyleCat State City       nBeersPerStylePerCi~ nBeers  brewPcap  X2018 stylePct meanPct sdPct
##    <chr>    <chr> <chr>                     <int>  <dbl>     <dbl>  <dbl>    <dbl>   <dbl> <dbl>
##  1 Ale      CA    Sacramento                    4      5   1.97e-6 508529      0.8     0.522 0.248
##  2 IPA      CA    Sacramento                   NA     NA   1.97e-6 508529      0       0.374 0.226
##  3 Lager    CA    Sacramento                    1      5   1.97e-6 508529      0.2     0.351 0.333
##  4 Other    CA    Sacramento                   NA     NA   1.97e-6 508529      0       0.401 0.236
##  5 Stout    CA    Sacramento                   NA     NA   1.97e-6 508529      0       0.194 0.173
##  6 Ale      MI    Detroit                       1      6   1.49e-6 672662      0.167   0.522 0.248
##  7 IPA      MI    Detroit                       2      6   1.49e-6 672662      0.333   0.374 0.226
##  8 Lager    MI    Detroit                       1      6   1.49e-6 672662      0.167   0.351 0.333
##  9 Other    MI    Detroit                       2      6   1.49e-6 672662      0.333   0.401 0.236
## 10 Stout    MI    Detroit                      NA     NA   1.49e-6 672662      0       0.194 0.173
## # ... with 15 more rows
```

Which of the underserved cities have style percentages that are less than a standard deviation under the national percentage? From the chart below, we should prioritize in the following order: producing Ale in Kansas City and Detroit, "Other" in Sacremento, Kansas City and Nashville, IPA in Sacremento and Nashville,Lager in Memphis, Nashbille and Kansas City, Stout in all the 5 cities.

```
ggplot(filterCity,aes(x=StyleCat)) + geom_point(aes(y=stylePct,col=City),size=3,position=position_jitte
   geom_point(aes(StyleCat,meanPct),size=1,data=stylePctByState)+geom_errorbar(aes(
  x=StyleCat,ymin= meanPct-sdPct,ymax=meanPct+sdPct
),data=stylePctByState)+ylab("Average Percentage of Style in a City")+
  xlab("Beer Style")+labs(title="Which Beer Style should we sell to which city?")
```



library(plotly) brewhist= ggplot(targetCities,aes(log(brewPcap),text=City)) + geom_histogram(bins=60)

```
ggplotly(brewhist)
```