Craft Beer Breweries

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Introduction

In the below report, we have been provided two data sets for various `beers` and the `breweries` that produce them in the US. Our team had to do an exploratory Data Analysis on the data provided to come up with useful insights. We were provided with two separate data sets, one with details of the beers and and the other with the details of the breweries around the USA. To analyze this ## Reproducible Research in R Please begin by reading the the README.md.All the details on the structure of project has been documented. ### Loading Packages for Analysis Below are the packages required for the analysis of the Craft Beer and Brewery study.

Loading the Datasets for Analysis

We were provided with 2 data sets (`beers` and `breweries`). The `breweries` dataset contains the count of breweries from 50 states of the US and the `beer` data set contains the details of the beers (Alcohol by Volume Content and International Bitterness unit)
`Note : Beers dataset contains a list of 2410 US craft beers and Breweries dataset contains 558 US breweries.` ***Region Data : This is the data set we created for analysis group the 50 states in US into 4 regions North Central,North East , South and West***

```
#Read in Core Data
Beers = read.csv("/Users/Kevin/Desktop/School/Doing Data Science/Project 1/Beers.csv", header = TRUE)
Breweries = read.csv("/Users/Kevin/Desktop/School/Doing Data Science/Project 1/Breweries.csv", header = TRUE)

#Bring in Region Data
RegionData = data.frame(State = state.abb, Region = state.region)
Breweries = left_join(Breweries,RegionData,by = "State")

#Handle NA and missing data by replacing with Regional Means
Breweries = sqldf('
      select
      "Brew_ID","Name","City","State",

      case when "State"  = "DC" then "South" else "Region" end as Region

      from
      Breweries
                 ')

Distilled_Data = merge(Beers,Breweries, by.x = "Brewery_id", by.y = "Brew_ID")
#Distilled_Data = left_join(Beers,Distilled_Data,by = "Beer_ID")

#Create table for IBU and ABV means by State and Region - excluding missing data
State_Means =
Distilled_Data[!is.na(Distilled_Data$ABV) & !is.na(Distilled_Data$IBU),] %>%
  group_by(State) %>%
  summarize(Mean_IBU_by_State = mean(IBU),
            Mean_ABV_by_State = mean(ABV))
Regional_Means =
  Distilled_Data[!is.na(Distilled_Data$ABV) & !is.na(Distilled_Data$IBU),] %>%
  group_by(Region) %>%
  summarize(Mean_IBU_by_Region = mean(IBU),
            Mean_ABV_by_Region = mean(ABV))

Distilled_Data = left_join(Distilled_Data,State_Means,by = "State")
Distilled_Data = left_join(Distilled_Data,Regional_Means,by = "Region")
```

3. Research Questions

We are now going to analyze the research questions for EDA ### 1. How many breweries are present in each state? Here we used the breweries dataset to count the number of breweries per state in the US. **Output : We were able to find Colorado and California to have the highest number of Craft breweries in US.**

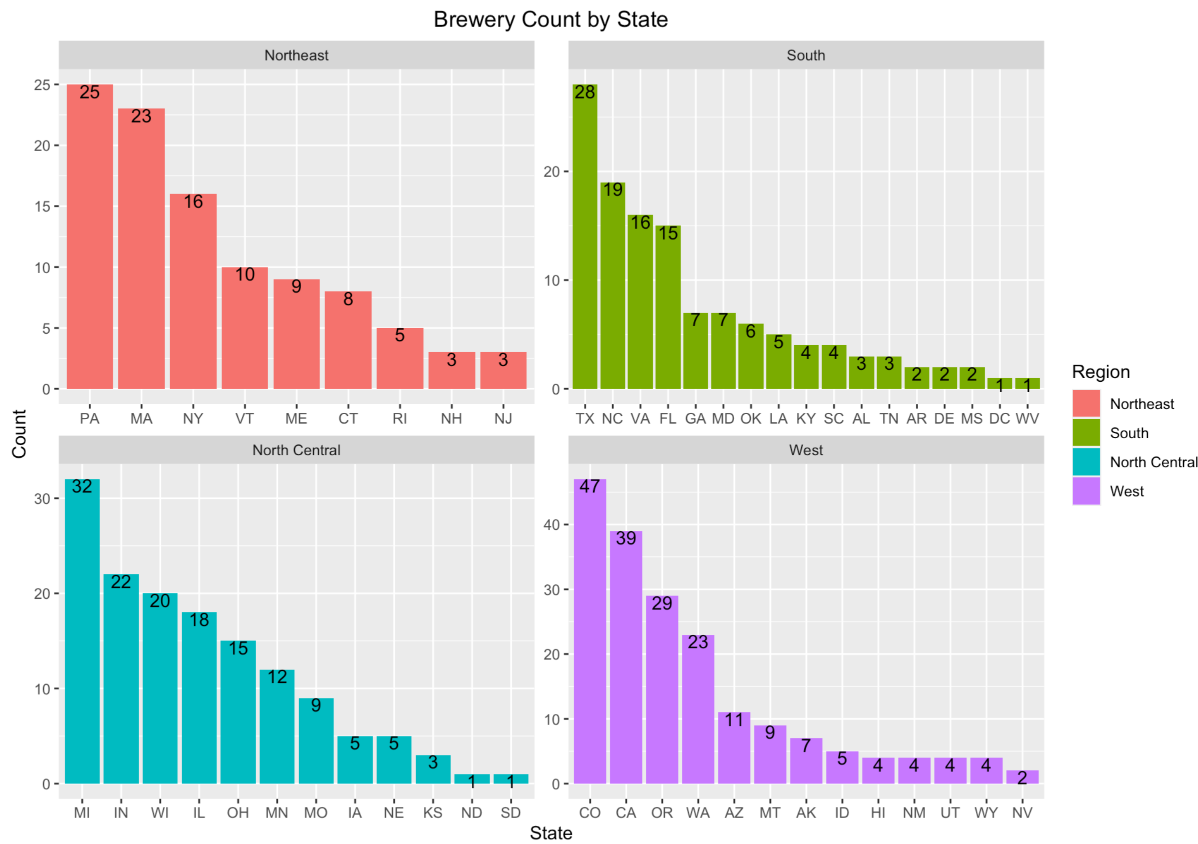
```
kable(count(Breweries,State))
```

State	n
AK	7
AL	3
AR	2

AZ	11
CA	39
CO	47
CT	8
DC	1
DE	2
FL	15
GA	7
HI	4
IA	5
ID	5
IL	18
IN	22
KS	3
KY	4
LA	5
MA	23
MD	7
ME	9
MI	32
MN	12
MO	9
MS	2
MT	9
NC	19
ND	1
NE	5
NH	3
NJ	3
NM	4
NV	2
NY	16
OH	15
OK	6
OR	29
PA	25
RI	5
SC	4
SD	1
TN	3
TX	28
UT	4
VA	16
VT	10
WA	23
WI	20
WV	1
WY	4

```
#Brewery Count by State
Breweries %>%
  group_by(State,Region) %>%
  summarize(Count = n()) %>%
  ggplot(aes(x = reorder(State,-Count), y = Count,fill=Region)) +
  geom_bar(stat = "identity") +
  geom_text(aes(label=Count),vjust=1) +
  ggtitle("Brewery Count by State",) + xlab("State") + ylab("Count") +
  facet_wrap(~Region, scales="free") +
  theme(plot.title=element_text(hjust=.5))
```

```
## `summarise()` has grouped output by 'State'. You can override using the `.groups` argument.
```



2. Merge beer data with the breweries data. Print the first 6 observations and the last six observations to check the merged file. Here we merged the both the data sets into a single data set `Distilled_Data` . By which we can find the beers made in by each state in United States. The Brewery_id column name in the Beers data was changed to Brew_id for merging both data sets #Address missing data and Plot Median ABV and Bitterness

```
kable(head(Distilled_Data))
```

Brewery_id	Name.x	Beer_ID	ABV	IBU	Style	Ounces	Name.y	City	State	Region	Mean_IBU_by_State	Mean_ABV_by_State	Mean_IBU_by_Region	Mea
1	Get Together	2692	0.045	50	American IPA	16	NorthGate Brewing	Minneapolis	MN	North Central	49.95652	0.0604348	39.19035	
1	Maggie's Leap	2691	0.049	26	Milk / Sweet Stout	16	NorthGate Brewing	Minneapolis	MN	North Central	49.95652	0.0604348	39.19035	
1	Wall's End	2690	0.048	19	English Brown Ale	16	NorthGate Brewing	Minneapolis	MN	North Central	49.95652	0.0604348	39.19035	
1	Pumpion	2689	0.060	38	Pumpkin Ale	16	NorthGate Brewing	Minneapolis	MN	North Central	49.95652	0.0604348	39.19035	
1	Stronghold	2688	0.060	25	American Porter	16	NorthGate Brewing	Minneapolis	MN	North Central	49.95652	0.0604348	39.19035	
1	Parapet ESB	2687	0.056	47	Extra Special / Strong Bitter (ESB)	16	NorthGate Brewing	Minneapolis	MN	North Central	49.95652	0.0604348	39.19035	

```
kable(tail(Distilled_Data))
```

	Brewery_id	Name.x	Beer_ID	ABV	IBU	Style	Ounces	Name.y	City	State	Region	Mean_IBU_by_State	Mean_ABV_by_State	Mean_IBU_by
2405	556	Pilsner Ukiah	98	0.055	NA	German Pilsener	12	Ukiah Brewing Company	Ukiah	CA	West	46.28148	0.0628889	4
2406	557	Heinnieweisse Weissebier	52	0.049	NA	Hefeweizen	12	Butternuts Beer and Ale	Garrattsville	NY	Northeast	46.00000	0.0604565	4
2407	557	Snapperhead IPA	51	0.068	NA	American IPA	12	Butternuts Beer and	Garrattsville	NY	Northeast	46.00000	0.0604565	4

							Ale						
2408	557	Moo Thunder Stout	500.049	NA	Milk / Sweet Stout	12	Butternuts Beer and Ale	Garrattsville	NY	Northeast	46.00000	0.0604565	4
2409	557	Porkslap Pale Ale	490.043	NA	American Pale Ale (APA)	12	Butternuts Beer and Ale	Garrattsville	NY	Northeast	46.00000	0.0604565	4
2410	558	Urban Wilderness Pale Ale	300.049	NA	English Pale Ale	12	Sleeping Lady Brewing Company	Anchorage	AK	West	40.88235	0.0561765	4

```
write.csv(Distilled_Data,"/Users/Kevin/Desktop/School/Doing Data Science/Project 1/Distilled_Data.csv")
write.csv(RegionData,"/Users/Kevin/Desktop/School/Doing Data Science/Project 1/Region_Data.csv")
```

3.Address the missing values in each column.

To proceed with data analysis we first inspected both the datasets for any missing value. **1.Beer Data set :** + International Bitterness Unit : Out of the 2410 beers - 1405 beers were missing IBU value + Alcohol By Volume : Out of the 2410 beers - 62 beers were missing ABV content value

2.Breweries Data set : + No missing data

To deal with this anomaly and unbiased data analysis we populated the missing values in the Beer Data. We populated the missing values with the mean of respective Region/State.

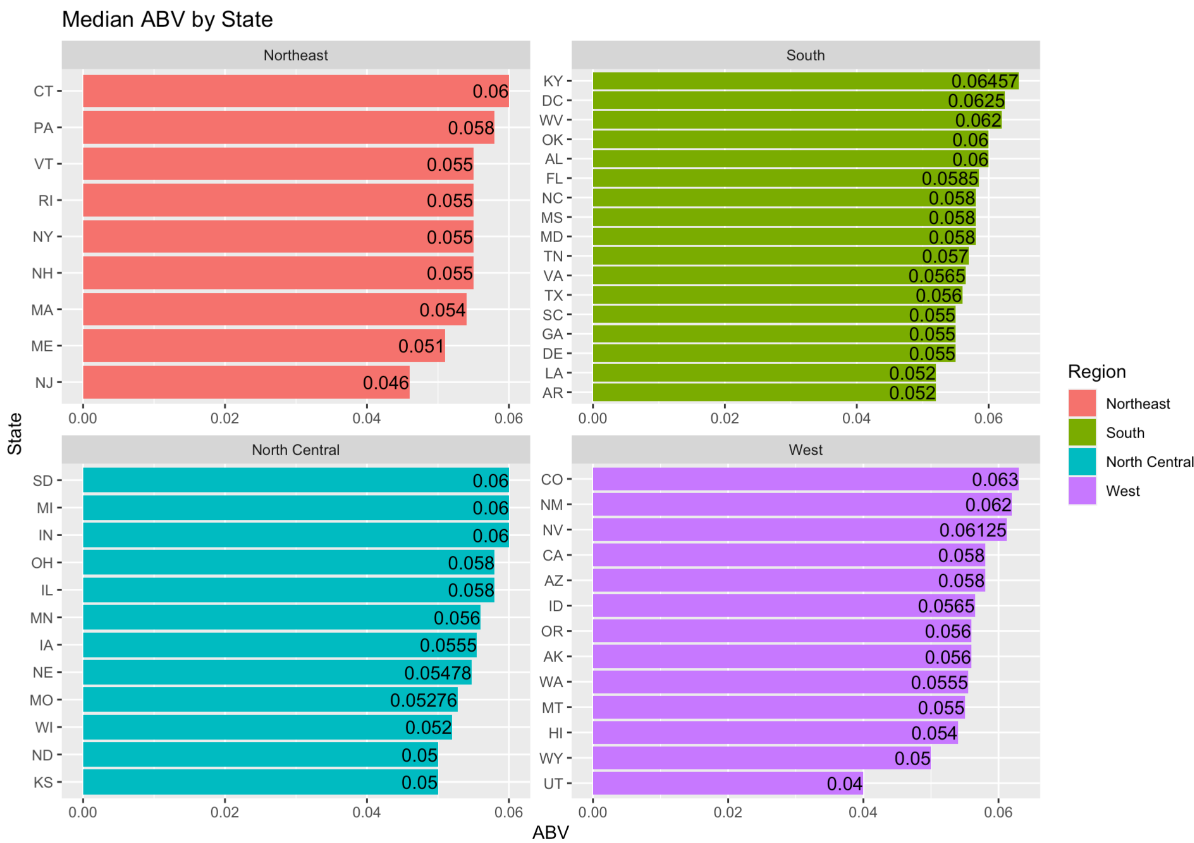
```
Distilled_Data2 = Distilled_Data

Distilled_Data2 =
Distilled_Data2 %>%
  mutate(ABV = coalesce(Distilled_Data2$ABV,Distilled_Data2$Mean_ABV_by_State),
         IBU = coalesce(coalesce(Distilled_Data2$IBU,Distilled_Data2$Mean_IBU_by_State),Distilled_Data2$Mean_IBU_
by_Region))
```

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

Calculation of the median Alcohol content of each state grouped by region ### +4a. Median Alcohol Content - After plotting we discovered that the state with the highest median ABV was Kentucky with an ABV of .064 hailing from the Southern Region. The median bitterness was highest in West Virginia again from the Southern Region.

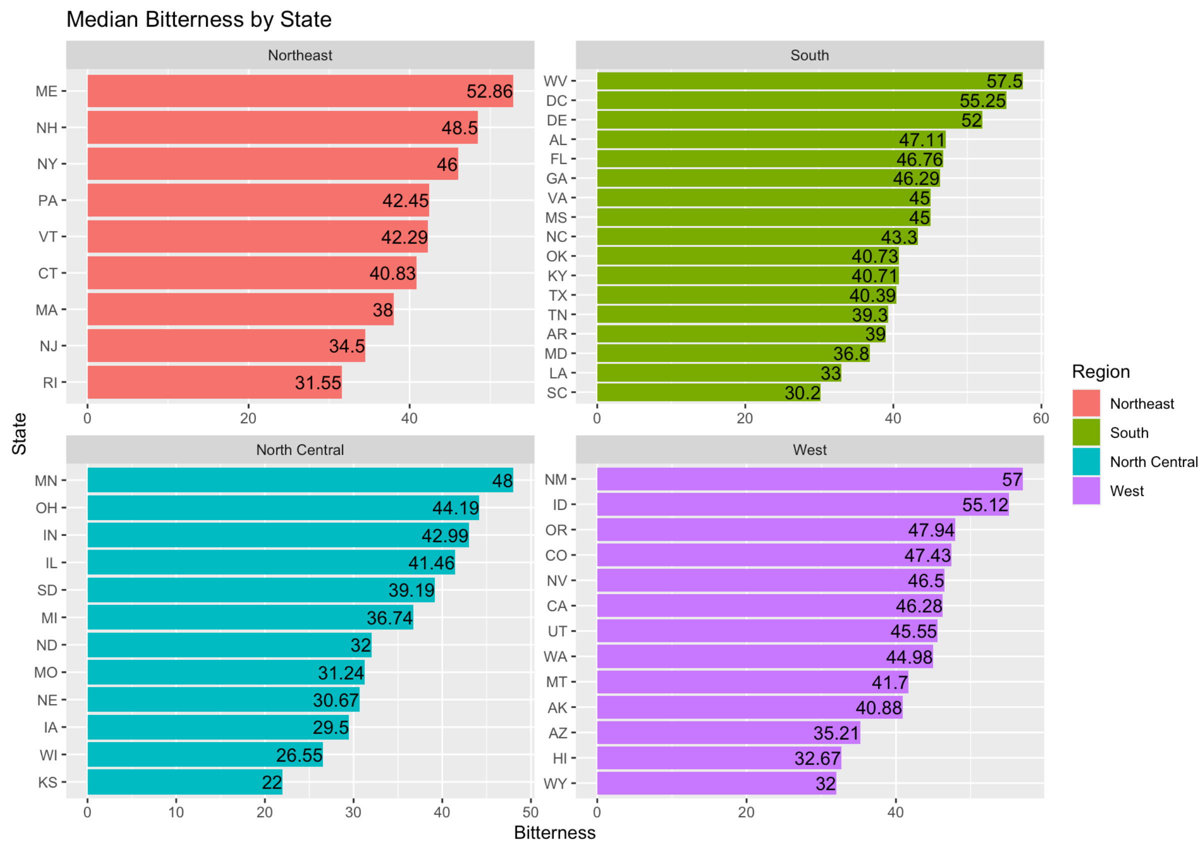
```
#Median ABV
Distilled_Data2 %>%
  group_by(State,Region) %>%
  summarize(
    Median_Alcohol_Content = round(median(ABV,na.rm=TRUE),digits=5),
    Median_Bitterness = median(IBU,na.rm=TRUE)
  ) %>%
  ggplot(aes(reorder(x = State,Median_Alcohol_Content), y = Median_Alcohol_Content,fill=Region)) + geom_bar(stat=
"identity") +
  xlab("State") + ylab("ABV") + ggtitle("Median ABV by State") + facet_wrap(~Region, scales="free") +
  geom_text(aes(label=round(Median_Alcohol_Content,digits=6)),hjust=1) +
  coord_flip()
```

```
## `summarise()` has grouped output by 'State'. You can override using the `.groups` argument.
```




```
#Median Bitterness
Distilled_Data2 %>%
  group_by(State,Region) %>%
  summarize(
    Median_Bitterness = median(IBU,na.rm=TRUE),
    Median_Alcohol_Content = median(ABV,na.rm=TRUE)
  ) %>%
  ggplot(aes(reorder(x = State,Median_Bitterness), y = Median_Bitterness,fill=Region)) + geom_bar(stat="identity"
) +
  xlab("State") + ylab("Bitterness") + ggtitle("Median Bitterness by State") + coord_flip() +
  geom_text(aes(label=round(Median_Bitterness,digits=2)),hjust=1) +
  facet_wrap(~Region, scales="free")
```

```
## `summarise()` has grouped output by 'State'. You can override using the `.groups` argument.
```



5.Which state has the maximum alcoholic (ABV) beer? Which state has the most bitter (IBU) beer? ### 5a. Most Alcoholic Beer in US ### Observation : Upon analysis the beer with maximum alcohol is made in the `Lee Hill Series Vol.5` made in Colorado West

5b. Most Bitter Beer in US

Observation : Upon analysis the beer with maximum bitter content is `Bitter Bitch Imperial IPA` made in Oregano in West Region

```
Top_ABV = Distilled_Data2[order(-Distilled_Data2$ABV),]
kable(head(Top_ABV,1))
```

	Brewery_id	Name.x	Beer_ID	ABV	IBU	Style	Ounces	Name.y	City	State	Region	Mean_IBU_by_State	Mean_ABV_by_State	Mean_IBU_by_Regior
375	52	Lee Hill Series Vol. 5 - Belgian Style Quadrupel Ale	2565	0.128	47.43151	Quadrupel (Quad)	19.2	Upslope Brewing Company	Boulder	CO	West	47.43151	0.0648356	45.5246

```
Most_Bitter = Distilled_Data2[order(-Distilled_Data2$IBU),]
kable(head(Most_Bitter,1))
```

	Brewery_id	Name.x	Beer_ID	ABV	IBU	Style	Ounces	Name.y	City	State	Region	Mean_IBU_by_State	Mean_ABV_by_State	Mean_IBU_by_Region	Mean_A
1857	375	Bitter Bitch Imperial IPA	980	0.082	138	American Double / Imperial IPA	12	Astoria Brewing Company	Astoria	OR	West	47.94253	0.0567011	45.52468	

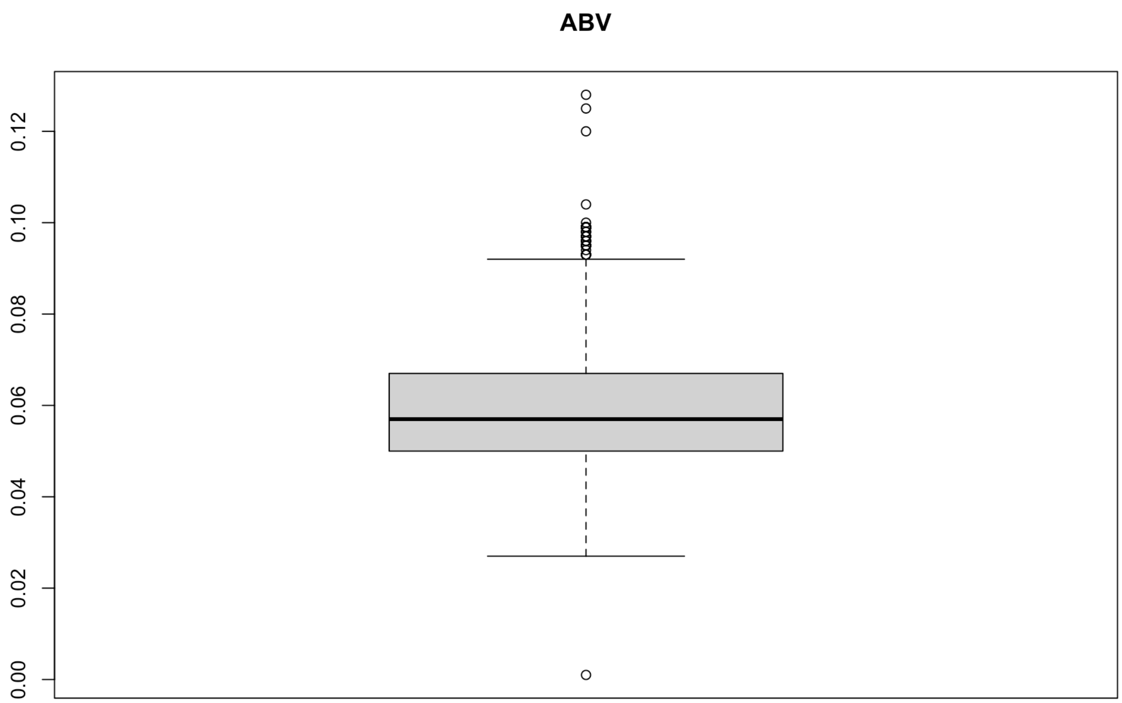
6. Comment on the summary statistics and distribution of the ABV variable.

Observation : The chart shows a right tailed distribution with the majority of alcohol content hovering between .05 and .06

```
summary(Distilled_Data2$ABV)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.00100 0.05000 0.05700 0.05979 0.06700 0.12800
```

```
boxplot(Distilled_Data2$ABV,main="ABV")
```

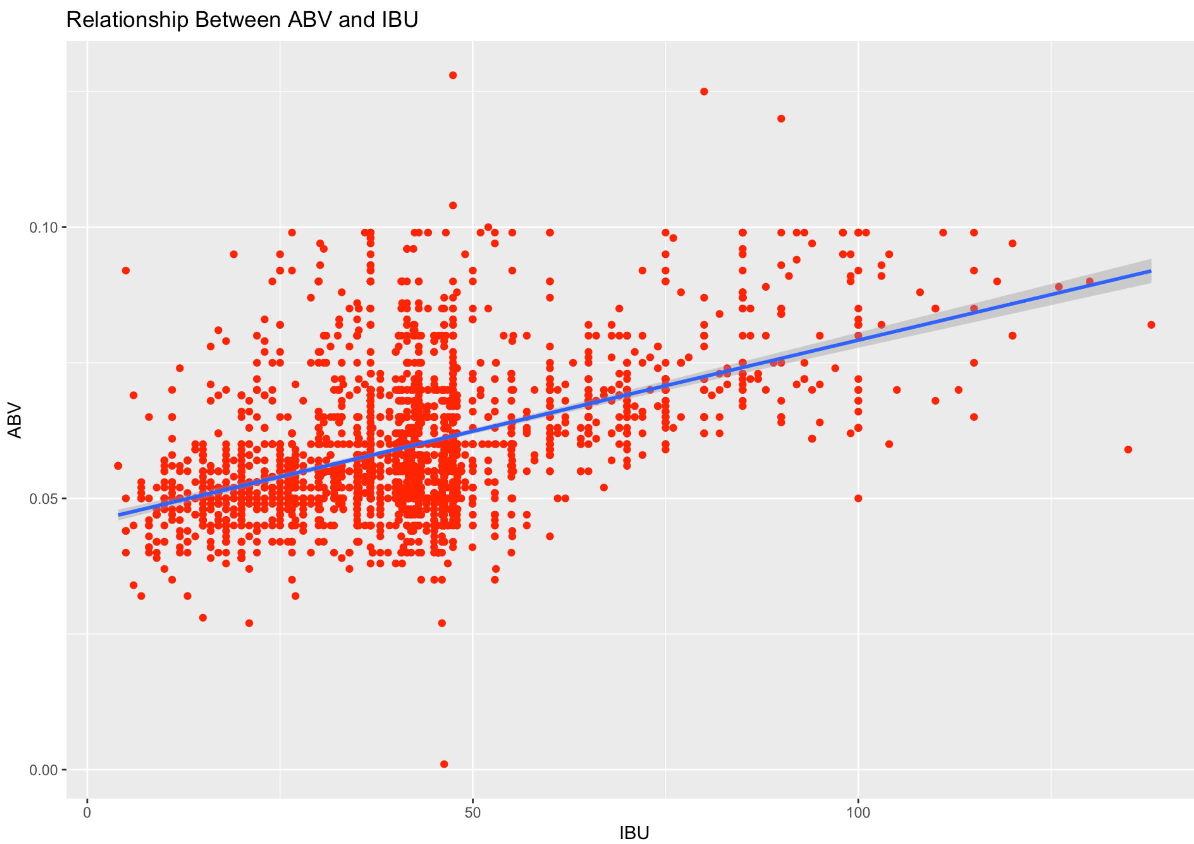


7. Is there an apparent relationship between the bitterness of the beer and its alcoholic content? Draw a scatter plot.

Observation : We observed a positive linear correlation between ABV and IBU. Overall, as the bitterness increased so did the alcohol content.

```
Distilled_Data2 %>% ggplot(aes(x=IBU, y=ABV)) + geom_point(color="red") + geom_smooth(method="lm") +
  ggtitle("Relationship Between ABV and IBU")
```

```
## `geom_smooth()` using formula 'y ~ x'
```

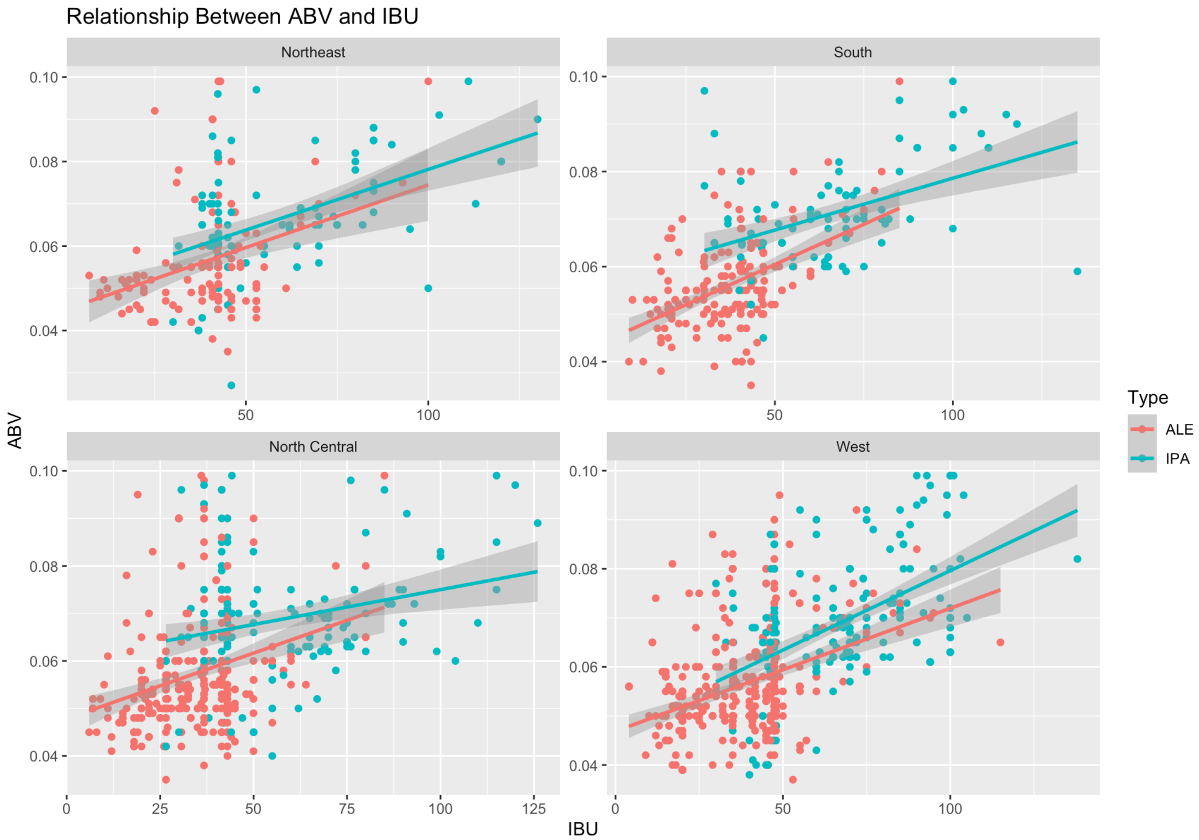


8. Use KNN to differentiate the beer from Ale or IPA Beer

Observation : First we had to filter the data set to only ALE and IPA beers then plot the relationship by region.

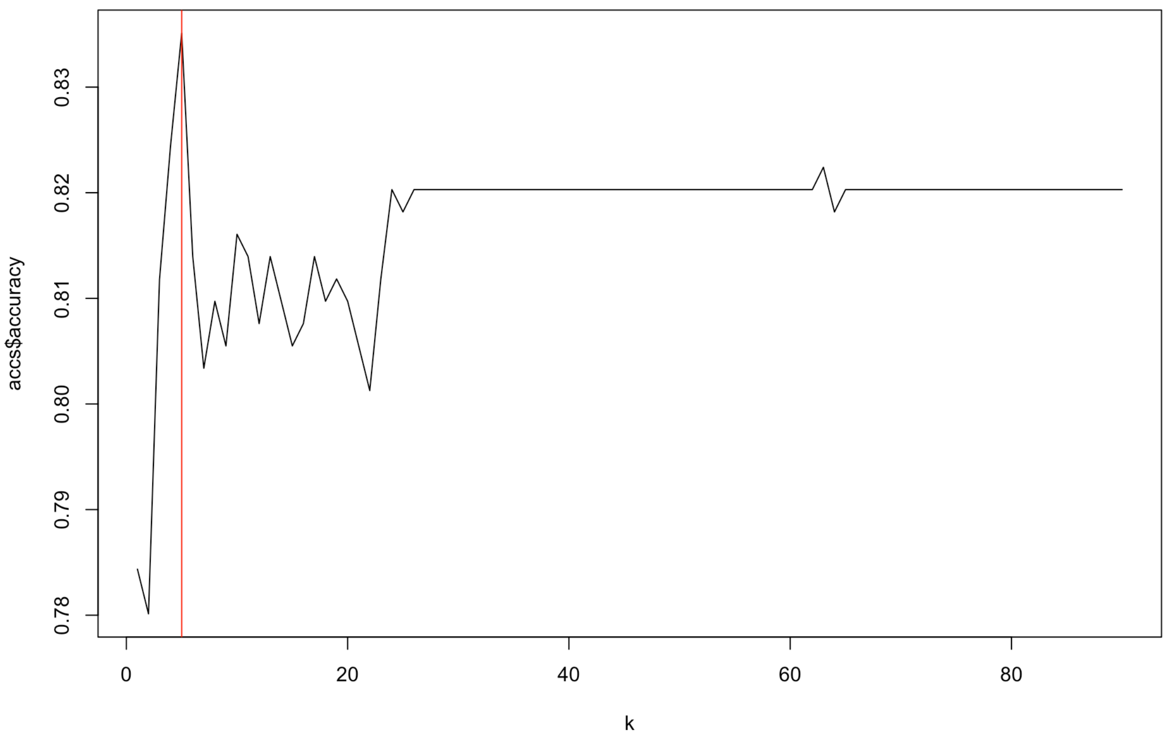
```
#Relationship Between IBU and ABV by Type
IPA_ALE = sqldf('
  select
  "Name","Style" as Style,"ABV","IBU","State","Region","City",
  case when "Style" like "%ALE%" then "ALE"
       when "Style" like "%IPA%" then "IPA" end as Type
 from
  Distilled_Data2
 where
  "Style" like "%ALE%" OR "Style" like "%IPA%"
 ')

IPA_ALE %>% ggplot(aes(x=IBU, y=ABV,color=Type)) + geom_point() + geom_smooth(method="lm") +
  ggtitle("Relationship Between ABV and IBU") +
  facet_wrap(~Region,scales="free")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



8b. Use KNN to differentiate the beer from ALE or IPA Beer ## Observation : Found optimal K in order to produce the most accurate KNN model. When k = 5 we were able to formulate an 84% accuracy using the variables ABV and IBU

```
splitPerc = .70
trainBeer = sample(1:dim(IPA_ALE)[1],round(splitPerc * dim(IPA_ALE)[1]))
train = IPA_ALE[trainBeer,]
test = IPA_ALE[-trainBeer,]

accs = data.frame(accuracy = numeric(90), k = numeric(90))

for(i in 1:90)
{
  classifications = knn(train[,c(3,4)],test[,c(3,4)],train$Type, prob = TRUE, k = i)
  table(test$Type,classifications)
  CM = confusionMatrix(table(test$Type,classifications))
  accs$accuracy[i] = CM$overall[1]
  accs$k[i] = i
}
plot(accs$k,accs$accuracy, type = "l", xlab = "k")
abline(v=accs$k[which.max(accs$accuracy)], col="red")
```




```
accs$k[which.max(accs$accuracy)]
```

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

```
splitPerc = .70
trainIndices = sample(1:dim(IPA_ALE)[1],round(splitPerc * dim(IPA_ALE)[1]))
train = IPA_ALE[trainIndices,]
test = IPA_ALE[-trainIndices,]

classification = knn(IPA_ALE[,c(3,4)],IPA_ALE[,c(3,4)],IPA_ALE$Type,prob = TRUE, k = 5)
table(classification,IPA_ALE$Type)
```

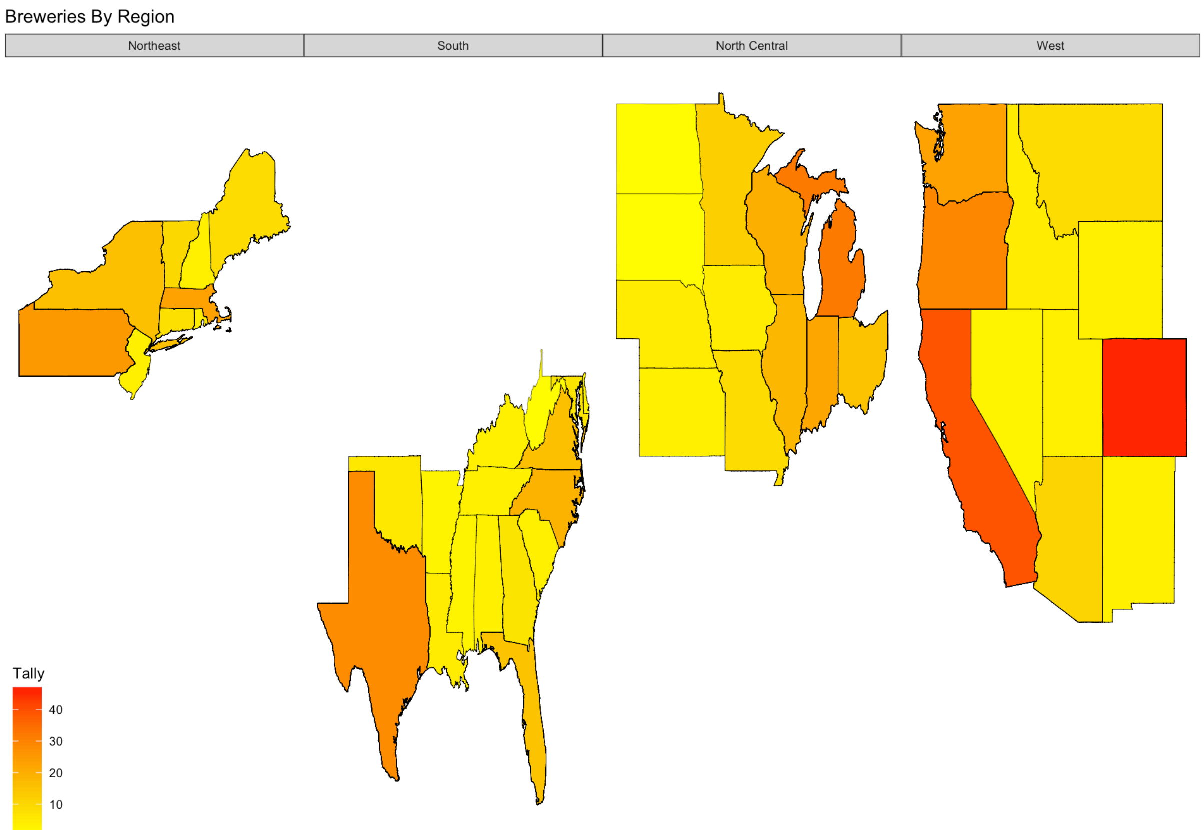
```
##
## classification ALE IPA
##            ALE 920 143
##            IPA 100 415
```

```
confusionMatrix(table(classification,IPA_ALE$Type))
```

```
## Confusion Matrix and Statistics
## 
## 
## classification ALE IPA
##            ALE 920 143
##            IPA 100 415
## 
##                Accuracy : 0.846
##                  95% CI : (0.8272, 0.8635)
##     No Information Rate : 0.6464
##     P-Value [Acc > NIR] : < 2.2e-16
## 
##                   Kappa : 0.6572
## 
##  Mcnemar's Test P-Value : 0.007054
## 
##             Sensitivity : 0.9020
##             Specificity : 0.7437
##          Pos Pred Value : 0.8655
##          Neg Pred Value : 0.8058
##              Prevalence : 0.6464
##          Detection Rate : 0.5830
##    Detection Prevalence : 0.6736
##       Balanced Accuracy : 0.8228
## 
##        'Positive' Class : ALE
## 
```

#Additional Insight on Craft beer's and breweries ## Observation : We found that the southern and western regions consume alcohol with higher bitterness and the northeast and northern regions prefer a less alcoholic content in their beer. The geographipal map of US shows the state groupings by regions.

```
map_data = map_data('state')
map_data = map_data %>% mutate(State = state2abbr(map_data$region))

Final_Breweries = left_join(Breweries,map_data, by = 'State')
Count_Breweries = Breweries %>%
  group_by(State) %>%
  summarize(Tally = n())

New_Breweries = left_join(Final_Breweries,Count_Breweries,by = 'State')
p0 <- ggplot(data = New_Breweries,
             mapping = aes(x = long, y = lat,
                           group = group,fill=Tally))
p1 <- p0 + geom_polygon(color = "black", size = 0.1) +
  theme_map() +
  scale_fill_gradient2(low = "green",
                       mid = "yellow",
                       high = "red") +
  ggtitle("Breweries By Region") +
  facet_grid(~Region, scales="free")
p1
```


Breweries By Region
Northeast
South
North Central
West
Tally
40
30
20
10