Case Study 1

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Abstract

Two data sets were provided to explore the relationship between the variables contained therein. ABV and IBU served as continous quantitative variables and geographic location of breweries, brewery names, and styles of beer served as discrete categorical variables. The relationship between IBU and ABV, especially with respect to beer styles, was found to be significant (Pearson r: 0.67, p-val <.0001). This was further confirmed by a knn machine learning model. Based on these insights, additional machine learning models were created to predict styles of beer given geographic location and vice-versa. We suggest that these models and insights be applied for R&D and marketing purposes.

Setting up

Loading necessary libraries

R Markdown

```
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --
```

```
## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.5     v dplyr   1.0.7
## v tidyr   1.1.3     v stringr 1.4.0
## v readr   2.0.1     v forcats 0.5.1
```

```
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(ggpubr)
library(class)
library(caret)
```

```
## Loading required package: lattice
```

```
##
## Attaching package: 'caret'
```

```
## The following object is masked from 'package:purrr':
##
##     lift
```

```
library(e1071)
library(rvest)
```

```
##
## Attaching package: 'rvest'

## The following object is masked from 'package:readr':
##
##     guess_encoding
```

reading in the data

```
beers <- read_csv("https://raw.githubusercontent.com/BivinSadler/MSDS_6306_Doing-Data-Science/Master/Uni
```

```
## Rows: 2410 Columns: 7

## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (2): Name, Style
## dbl (5): Beer_ID, ABV, IBU, Brewery_id, Ounces

##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
breweries <- read_csv("https://raw.githubusercontent.com/BivinSadler/MSDS_6306_Doing-Data-Science/Maste
```

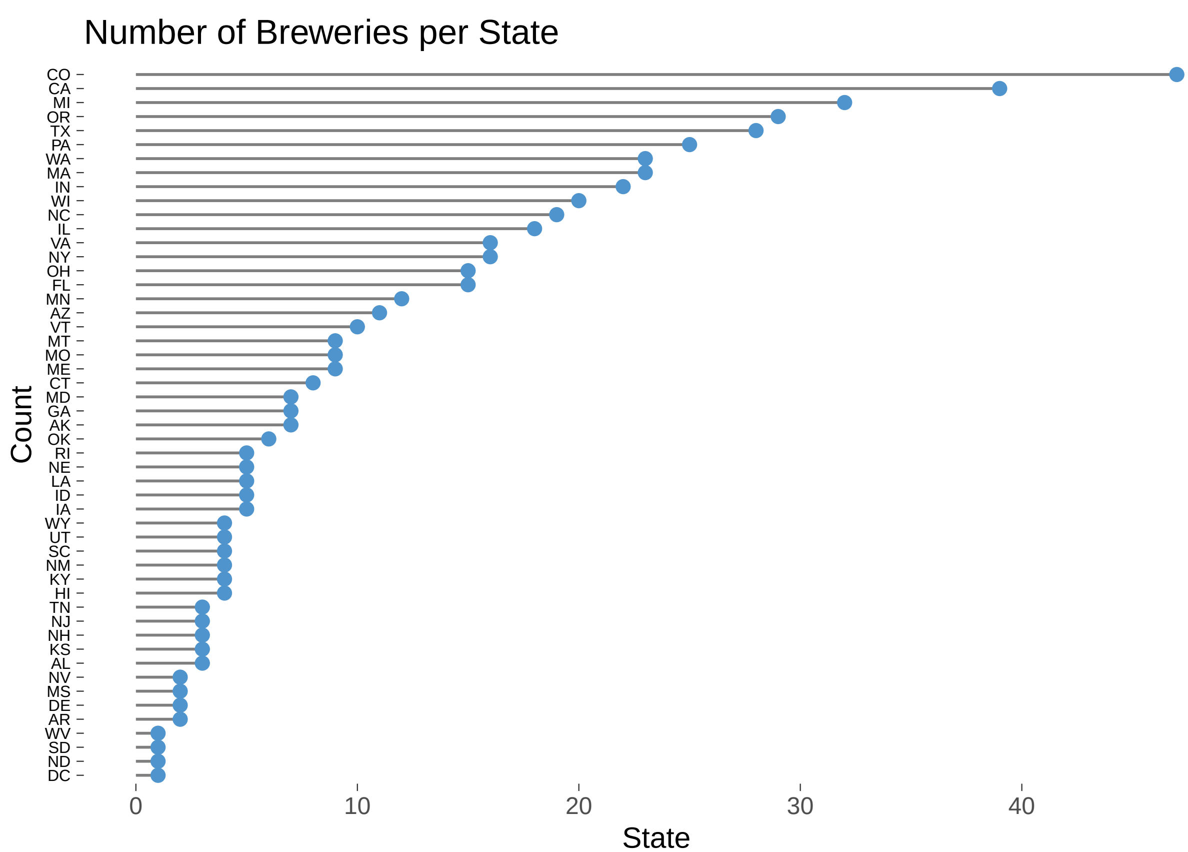
```
## Rows: 558 Columns: 4

## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (3): Name, City, State
## dbl (1): Brew_ID

##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Breweries per State

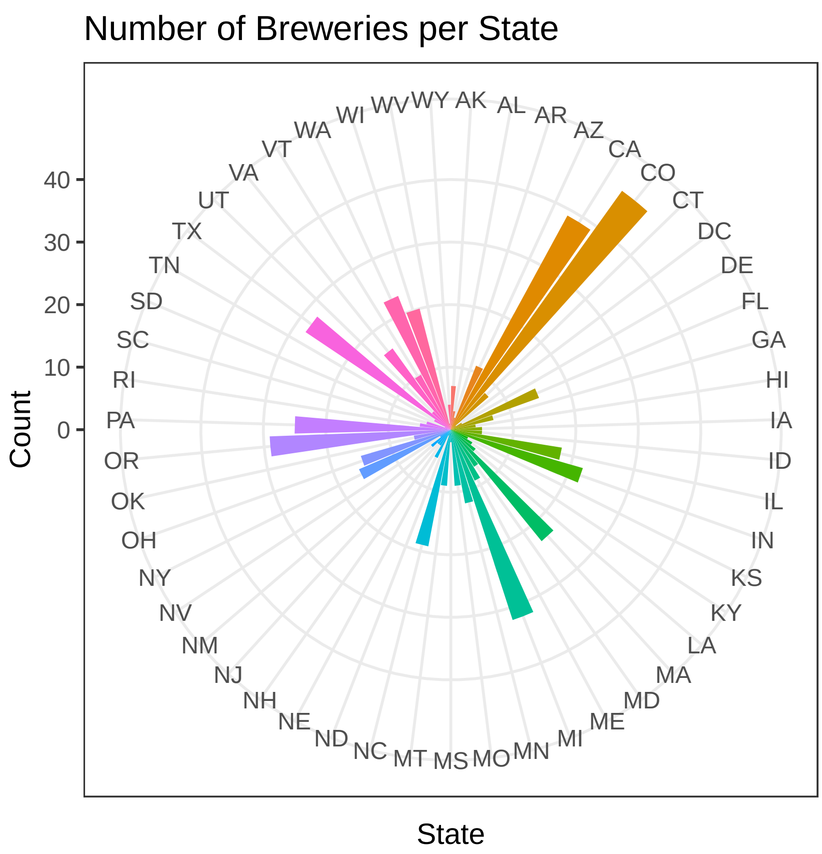
```
##How many breweries are present in each state?
#This table outlines the quantity of breweries in each state and will be used as the basis of the follo
numbystate <- data.frame(breweries %>% count(State))
numbystate
```

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

```r
numbystate$State <- as.factor(numbystate$State)

#bar graph depicting the number of breweries in each state
numbystate %>% ggplot(aes(x = reorder(State, n), y = n)) +
  geom_segment(aes(xend=State, yend=0), color = 'grey50') +
  geom_point(size=2, color="steelblue3") +
  coord_flip() +
  theme(legend.position = "none") +
  theme(axis.text.y = element_text(size = 6, color = "black")) +
  theme(panel.background = element_rect(fill = "white")) +
  theme(axis.ticks = element_line(size = .2)) +
  labs(x = "Count", y = "State") +
  ggtitle("Number of Breweries per State")
```




```r
#Different chart (polar coordinates) giving a better visualization of relative amount of breweries in e

numbystate %>% ggplot(aes(x = State, y = n, fill = State)) +
  geom_bar(stat = 'identity') +
  coord_polar() + theme_bw() +
  theme(legend.position = "none") +
  labs(x = "State", y = "Count") + ggtitle("Number of Breweries per State")
```

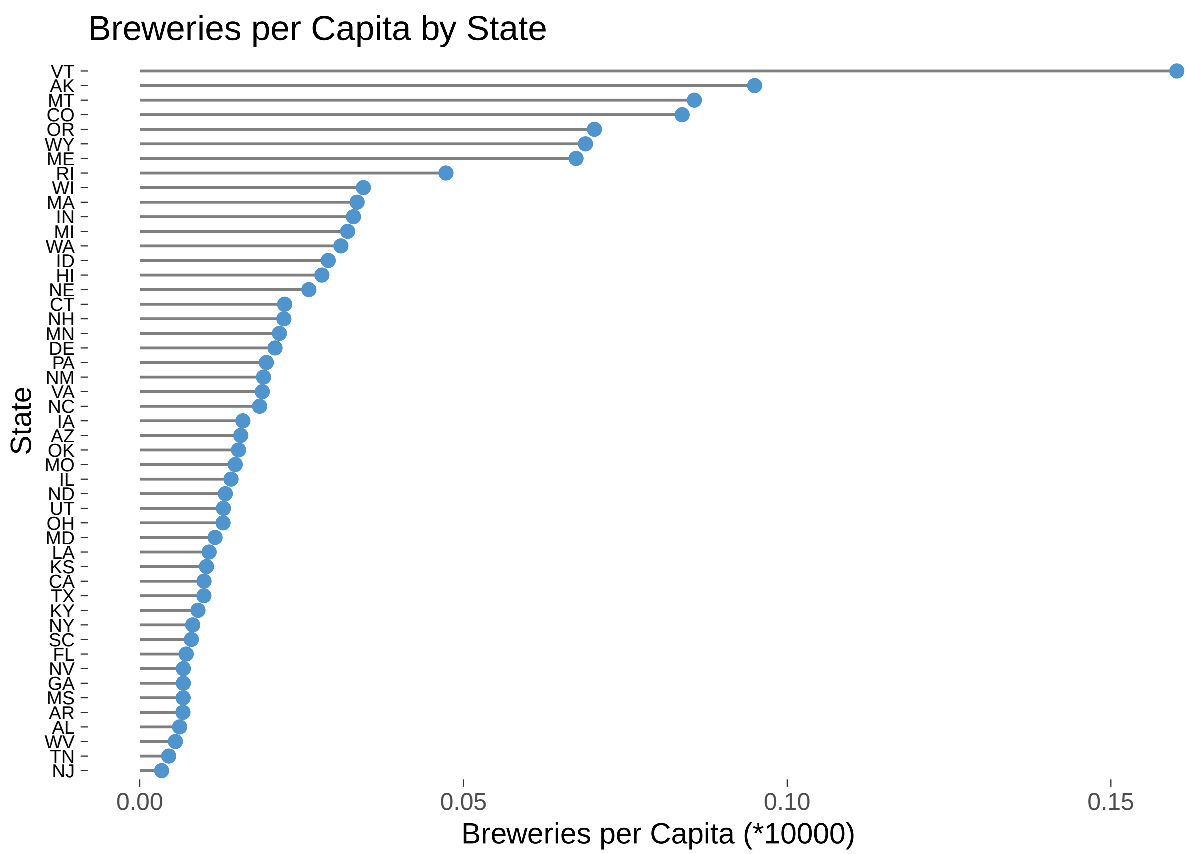



```r
## A more accurate representation of brewery density is depicted by determining Breweries per Capita. Da

statepop <- read_csv("https://raw.githubusercontent.com/j-dominguez9/Case-Study-1/main/Code/Tables/state
```

```
## Rows: 50 Columns: 2

## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (1): State
## dbl (1): population

##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
#Join census data with previous table(numbystate)
breweriespercapita <- full_join(numbystate, statepop, by = "State") %>%
  mutate(bpc = (n/population)*10000) %>%
  mutate(State = as.factor(State))

#Plot
breweriespercapita %>% filter(!is.na(population)) %>% filter(!State == "SD") %>%
  ggplot(aes(x = reorder(State, bpc), y = bpc)) +
  geom_segment(aes(xend=State, yend=0), color = 'grey50') +
```

```
  geom_point(size=2, color="steelblue3") +
  coord_flip() +
  theme(legend.position = "none") +
  theme(axis.text.y = element_text(size = 7, color = "black")) +
  theme(panel.background = element_rect(fill = "white")) +
  theme(axis.ticks = element_line(size = .2)) +
  ggtitle("Breweries per Capita by State") +
  labs(x = "State", y = "Breweries per Capita (*10000)")
```



Addressing Missing Values

```
##Address the missing values in each column.
sum(is.na(breweries))
```

```
## [1] 0
```

```
#As we can see, the breweries data set holds no missing values, thus no need to eliminate any missing v

sum(is.na(beers))
```

```
## [1] 1072
```

```
#The beers dataset has 1072, so we must eliminate noted values.

beers_clean <- beers %>% filter(!is.na(Name)) %>% filter(!is.na(Beer_ID)) %>%
```

```
  filter(!is.na(ABV)) %>% filter(!is.na(IBU)) %>%
  filter(!is.na(Brewery_id)) %>% filter(!is.na(Style)) %>%
  filter(!is.na(Ounces))

#Removed 1007 rows due to missing values.
```

Median ABV and IBU

```
##Compute the median alcohol content and international bitterness unit for each state. Plot a bar chart

#In order to join the two data sets successfully, we will need to find a primary key and a foreign key

colnames(breweries)
```

```
## [1] "Brew_ID" "Name"    "City"    "State"
```

```
colnames(beers_clean)
```

```
## [1] "Name"       "Beer_ID"    "ABV"        "IBU"        "Brewery_id"
## [6] "Style"      "Ounces"
```

```
#As we can see, Brewery ID would be a good key to join them; however, we must make sure that they have

breweries$Brewery = breweries$Name
breweries$Brewery_id = breweries$Brew_ID
head(breweries)
```

```
## # A tibble: 6 x 6
##   Brew_ID Name                       City          State Brewery       Brewery_id
##     <dbl> <chr>                      <chr>         <chr> <chr>              <dbl>
## 1       1 NorthGate Brewing          Minneapolis   MN    NorthGate Br~          1
## 2       2 Against the Grain Brewery Louisville    KY    Against the ~          2
## 3       3 Jack's Abby Craft Lagers   Framingham    MA    Jack's Abby ~          3
## 4       4 Mike Hess Brewing Company San Diego     CA    Mike Hess Br~          4
## 5       5 Fort Point Beer Company    San Francisco CA    Fort Point B~          5
## 6       6 COAST Brewing Company      Charleston    SC    COAST Brewin~          6
```

```
#Let's create a new dataframe with the relevant columns from 'breweries' before joining.

breweries_clean <- breweries %>% select(Brewery, City, State, Brewery_id)
join <- inner_join(breweries_clean, beers_clean, by = "Brewery_id")
head(join)
```

```
## # A tibble: 6 x 10
##   Brewery    City    State Brewery_id Name   Beer_ID   ABV   IBU Style        Ounces
##   <chr>      <chr>   <chr>      <dbl> <chr>    <dbl> <dbl> <dbl> <chr>         <dbl>
## 1 NorthGat~ Minne~ MN             1 Get T~    2692 0.045    50 American ~      16
## 2 NorthGat~ Minne~ MN             1 Maggi~    2691 0.049    26 Milk / Sw~      16
## 3 NorthGat~ Minne~ MN             1 Wall'~    2690 0.048    19 English B~      16
```

```
## 4 NorthGat~ Minne~ MN             1 Pumpi~    2689 0.06     38 Pumpkin A~     16
## 5 NorthGat~ Minne~ MN             1 Stron~    2688 0.06     25 American ~     16
## 6 NorthGat~ Minne~ MN             1 Parap~    2687 0.056    47 Extra Spe~     16
```

```
tail(join)
```

```
## # A tibble: 6 x 10
##   Brewery    City   State Brewery_id Name     Beer_ID   ABV   IBU Style   Ounces
##   <chr>      <chr>  <chr>      <dbl> <chr>      <dbl> <dbl> <dbl> <chr>    <dbl>
## 1 Pyramid B~ Seatt~ WA           545 Pyramid~     399 0.052    18 Hefewe~     12
## 2 Pyramid B~ Seatt~ WA           545 Haywire~      82 0.052    18 Hefewe~     16
## 3 Lancaster~ Lanca~ PA           546 Rumspri~     392 0.066    30 Maiboc~     12
## 4 Lancaster~ Lanca~ PA           546 Lancast~     195 0.048    28 Kölsch      12
## 5 Upstate B~ Elmira NY           547 Common ~     382 0.053    22 Americ~     16
## 6 Upstate B~ Elmira NY           547 Upstate~     381 0.065    70 Americ~     12
```

```
#From the joined data frame, let's select the relevant columns.

medABVIBU <- join %>% select(State, ABV, IBU)
head(medABVIBU)
```

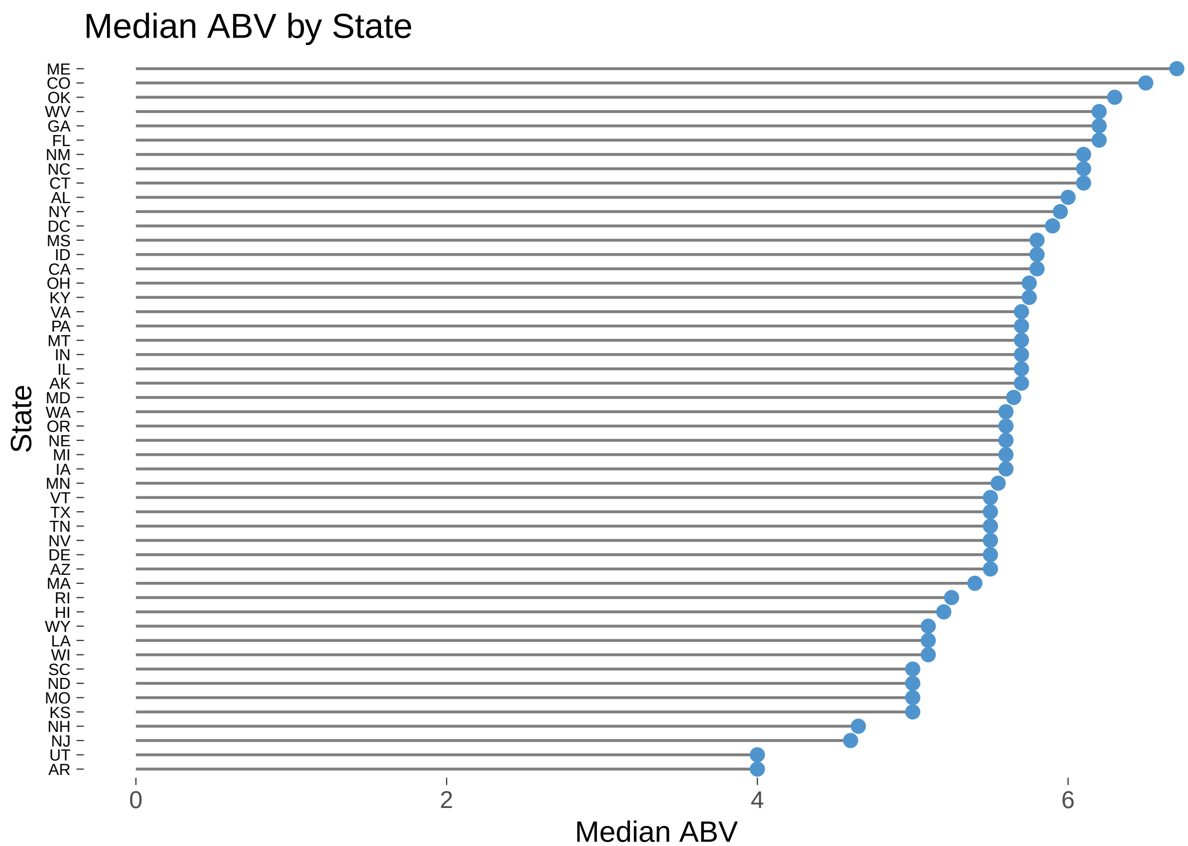
```
## # A tibble: 6 x 3
##   State   ABV   IBU
##   <chr> <dbl> <dbl>
## 1 MN    0.045    50
## 2 MN    0.049    26
## 3 MN    0.048    19
## 4 MN    0.06     38
## 5 MN    0.06     25
## 6 MN    0.056    47
```

```
#Having the relevant columns to work with, lets create a new one with the median ABV of each state and
medABV <- medABVIBU %>% group_by(State) %>% mutate(medianABV = median(ABV)*100) %>% select(State, media
head(medABV)
```

```
## # A tibble: 6 x 2
## # Groups:   State [6]
##   State medianABV
##   <chr>     <dbl>
## 1 AK          5.7
## 2 AL          6
## 3 AR          4
## 4 AZ          5.5
## 5 CA          5.8
## 6 CO          6.5
```

```
##Data set is now ready to plot.

medABV %>% ggplot(aes(x = reorder(State, medianABV), y = medianABV)) +
geom_segment(aes(xend=State, yend=0), color = 'grey50') +
  geom_point(size=2, color="steelblue3") +
  coord_flip() +
```

```r
  theme(legend.position = "none") +
  theme(axis.text.y = element_text(size = 6, color = "black")) +
  theme(panel.background = element_rect(fill = "white")) +
  theme(axis.ticks = element_line(size = .2)) +
  labs(x = "State", y = "Median ABV") +
  ggtitle("Median ABV by State")
```

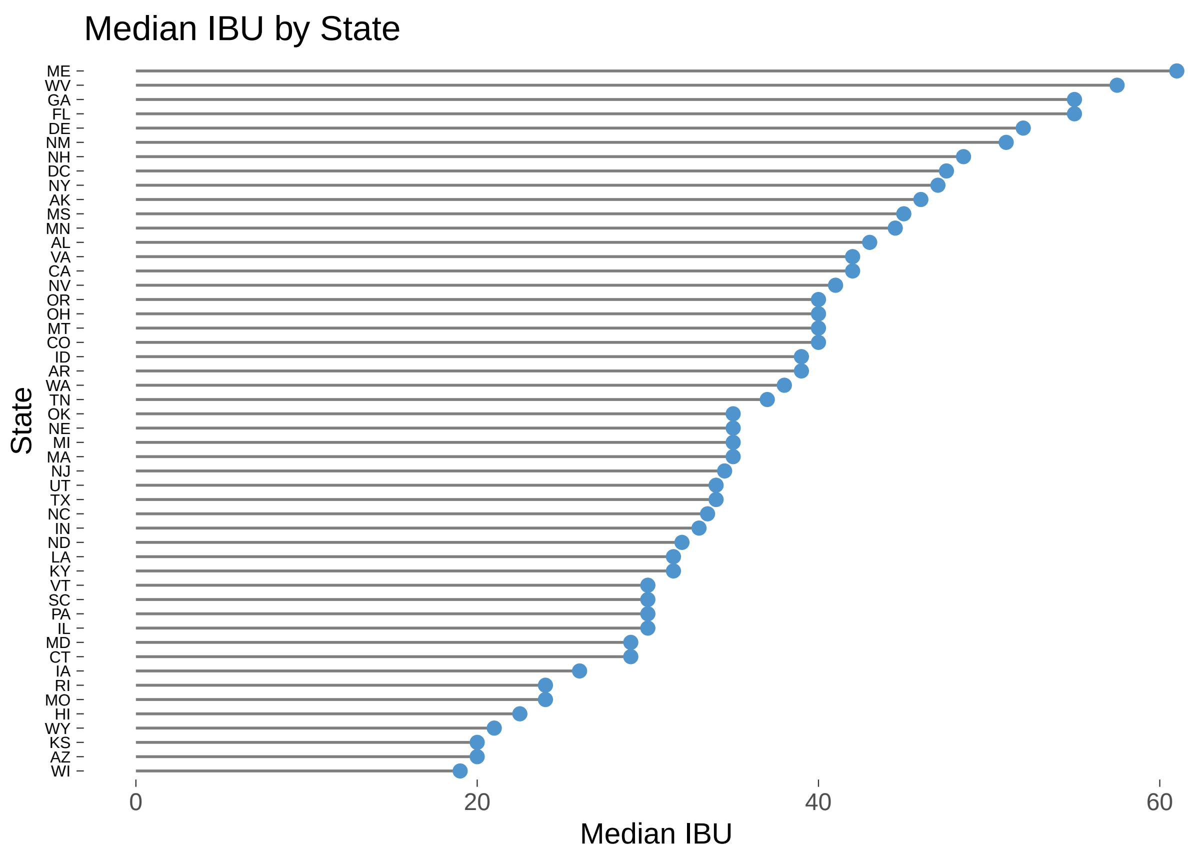



```r
##We will follow a similar process to derive median IBU by State.

medIBU <- medABVIBU %>%
  group_by(State) %>%
  mutate(medianIBU = median(IBU)) %>%
  select(State, medianIBU) %>%
  arrange(State) %>%
  distinct(State, medianIBU)

head(medIBU)
```

```
## # A tibble: 6 x 2
## # Groups:   State [6]
##   State medianIBU
##   <chr>     <dbl>
## 1 AK           46
## 2 AL           43
## 3 AR           39
```

```
## 4 AZ            20
## 5 CA            42
## 6 CO            40
```

```
#And plot in a similar manner.

medIBU %>% ggplot(aes(x = reorder(State, medianIBU), y = medianIBU)) +
 geom_segment(aes(xend=State, yend=0), color = 'grey50') +
  geom_point(size=2, color="steelblue3") +
  coord_flip() +
  theme(legend.position = "none") +
  theme(axis.text.y = element_text(size = 6, color = "black")) +
  theme(panel.background = element_rect(fill = "white")) +
  theme(axis.ticks = element_line(size = .2)) +
  labs(x = "State", y = "Median IBU") +
  ggtitle("Median IBU by State")
```



Max ABV and IBU

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

#We will create a new data frame with relevant columns to explore this question.
maxABVIBU <- join %>% select(Brewery, Name, State, ABV, IBU)
```

```r
#We need to identify the highest ABV level
max(maxABVIBU$ABV)
```

```
## [1] 0.125
```

```r
maxABVIBU %>% filter(ABV == "0.125")
```

```
## # A tibble: 1 x 5
##   Brewery                   Name           State   ABV   IBU
##   <chr>                     <chr>          <chr> <dbl> <dbl>
## 1 Against the Grain Brewery London Balling KY    0.125    80
```

```r
## We can see that the beer with the highest ABV belongs to the state of Kentucky (KY) with an ABV of 1

#We follow the same process for IBU.
max(maxABVIBU$IBU)
```

```
## [1] 138
```

```r
maxABVIBU %>% filter(IBU == "138")
```

```
## # A tibble: 1 x 5
##   Brewery                 Name                      State   ABV   IBU
##   <chr>                   <chr>                     <chr> <dbl> <dbl>
## 1 Astoria Brewing Company Bitter Bitch Imperial IPA OR    0.082   138
```

```r
#The beer with the highest IBU belongs to the state of Oregon (OR) with an IBU of 138. The beer is "Bit
```

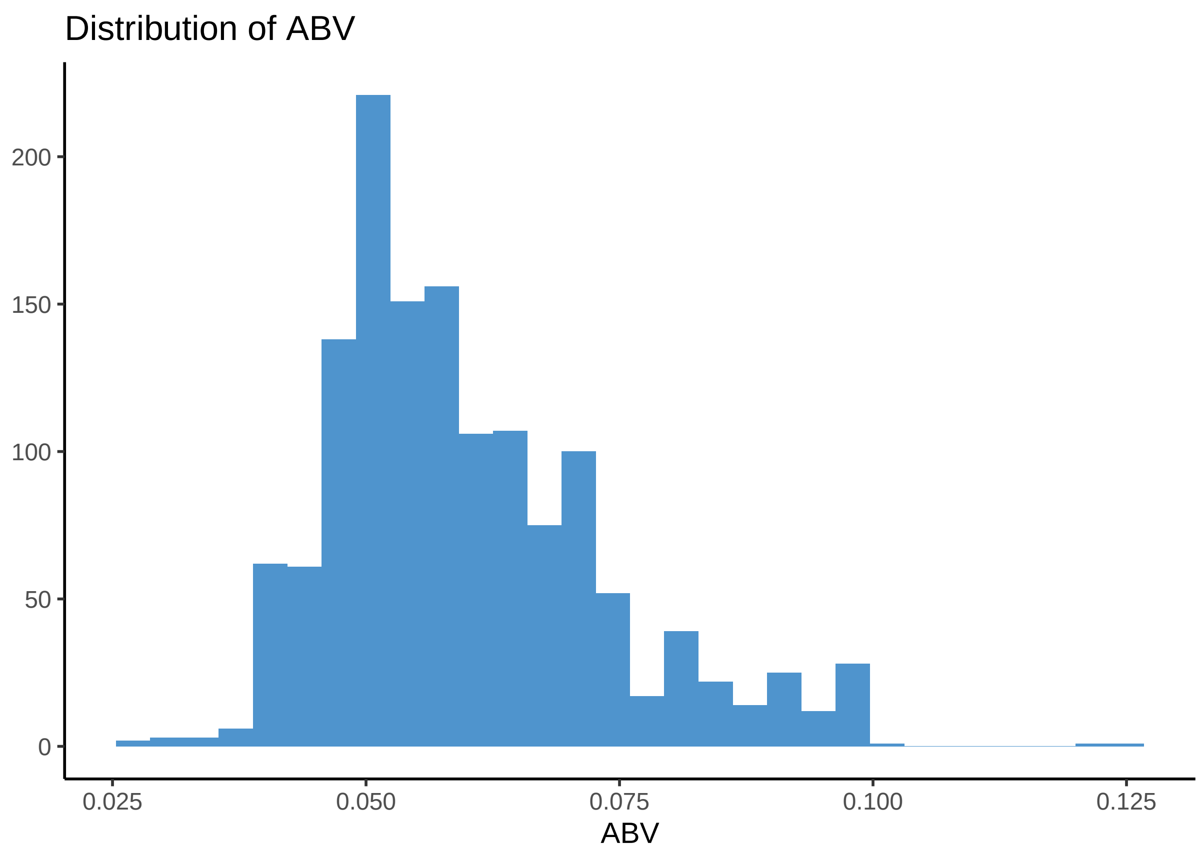
Summary and Distribution of ABV

```r
summary(maxABVIBU$ABV)
```

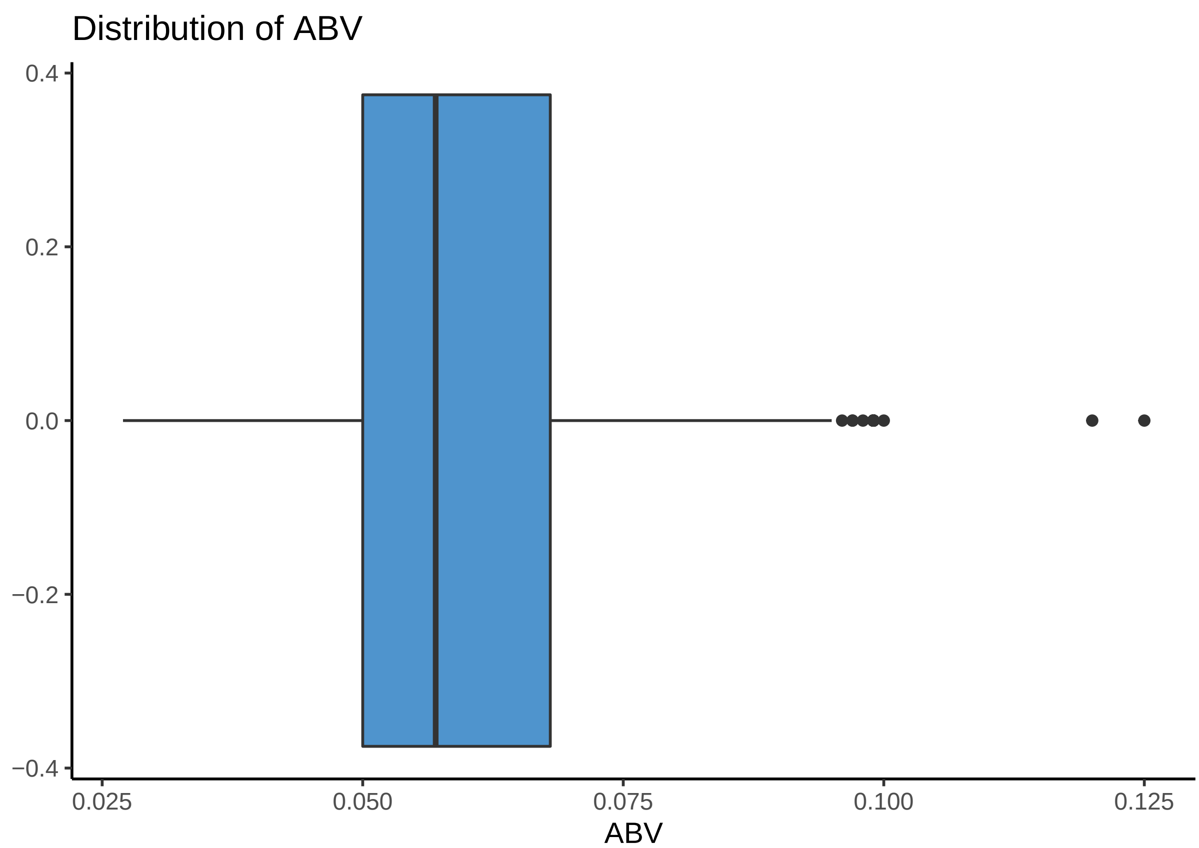
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.02700 0.05000 0.05700 0.05992 0.06800 0.12500
```

```r
#Histogram
maxABVIBU %>% ggplot(aes(x = ABV)) +
  geom_histogram(fill = "steelblue3") +
  theme_classic() +
  labs(x = "ABV", y = "") +
  ggtitle("Distribution of ABV")
```

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




```r
#Boxplot
maxABVIBU %>% ggplot(aes(x = ABV)) +
  geom_boxplot(fill = "steelblue3") +
  theme_classic() +
  labs(x = "ABV", y = "") +
  ggtitle("Distribution of ABV")
```

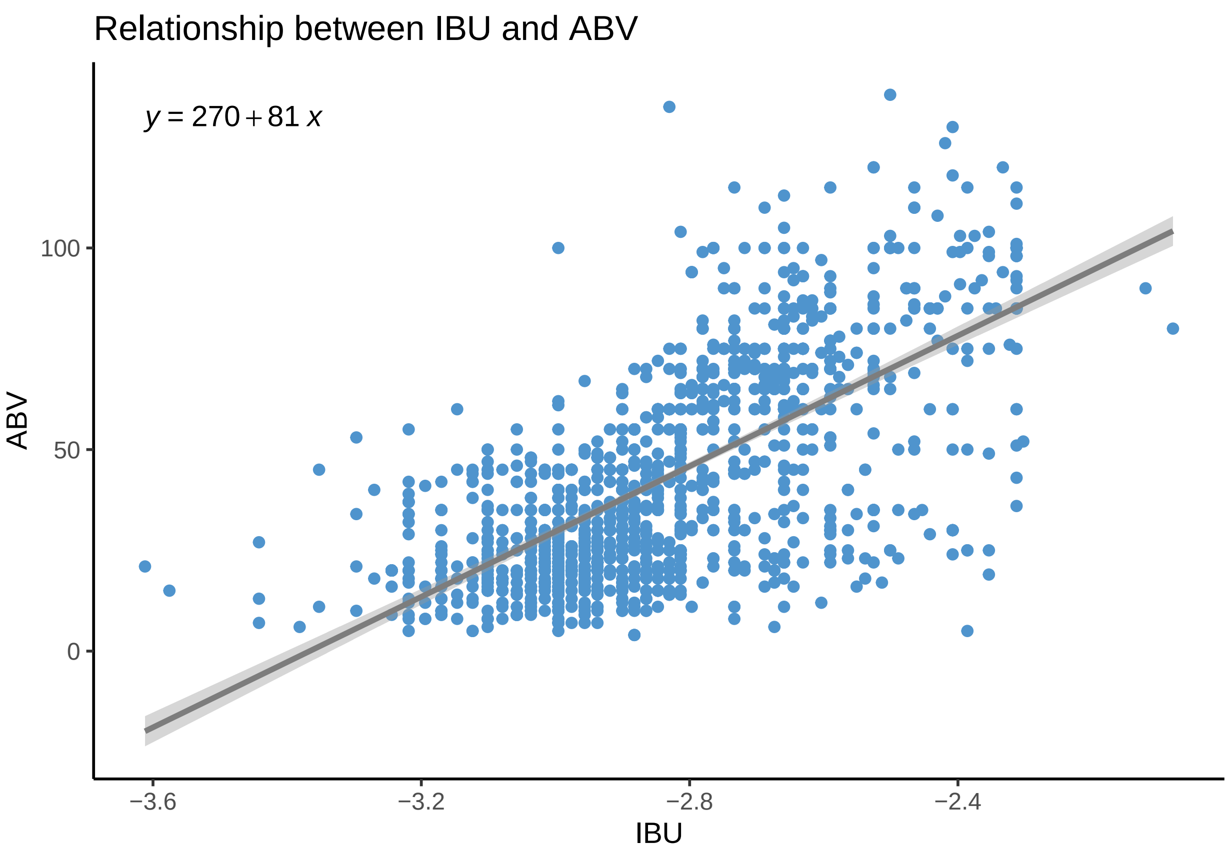



```
#Through visual inspection, we can see a right skew distribution in ABV. A log transformation may be ap
```

```
#As we saw earlier, the distributions of both the IBU and ABV columns were right skewed, it'd be helpfu

maxABVIBU %>% ggplot(aes(x = log(ABV), y = IBU)) +
  geom_point(color = "steelblue3") +
  geom_smooth(method = "lm", color = "grey49") +
  stat_regline_equation() +
  theme_classic() +
  labs(x = "IBU", y = "ABV") +
  ggtitle("Relationship between IBU and ABV")
```

The ABV variable has a right-skewed distribution, which would imply that more than half of the values fall below the mean 5.99%. We also see that the mean is larger than the median, which implies a right-skewed distribution. However, the summary statistics and histogram show us that the skewness is likely due to the upper outliers in the dataset. This is also apparent when we see the additional boxplot provided.

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




```
##From a visual inspection as well as a simple linear regression model, we can say that there is an appa
cor.test(x = log(maxABVIBU$ABV), y = maxABVIBU$IBU)
```

```
##
##  Pearson's product-moment correlation
##
## data:  log(maxABVIBU$ABV) and maxABVIBU$IBU
## t = 34.032, df = 1401, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.6430317 0.7004025
## sample estimates:
##       cor
## 0.6727271
```

```
#This Pearson's correlation provides overwhelming evidence that there is a positive linear relationship
```

Based on the generated scatterplot and Pearson's r at 0.67, we know that ABV and IBU have a medium to high positive correlation. This means that higher values of ABV are associated with higher values of IBU and that lower values of ABV are associated with lower values of IBU.

Please note that, although we observe a strong association between the two variables, we are not making any claims about the direction of the effect.

Next, we decide to use a KNN classification model to investigate the relationship between IBU and ABV in IPAs and other types of Ales.

```
#first, we create the data frames to be able to create the models.

sum(grepl("Ale", join$Style))
```

```
## [1] 559
```

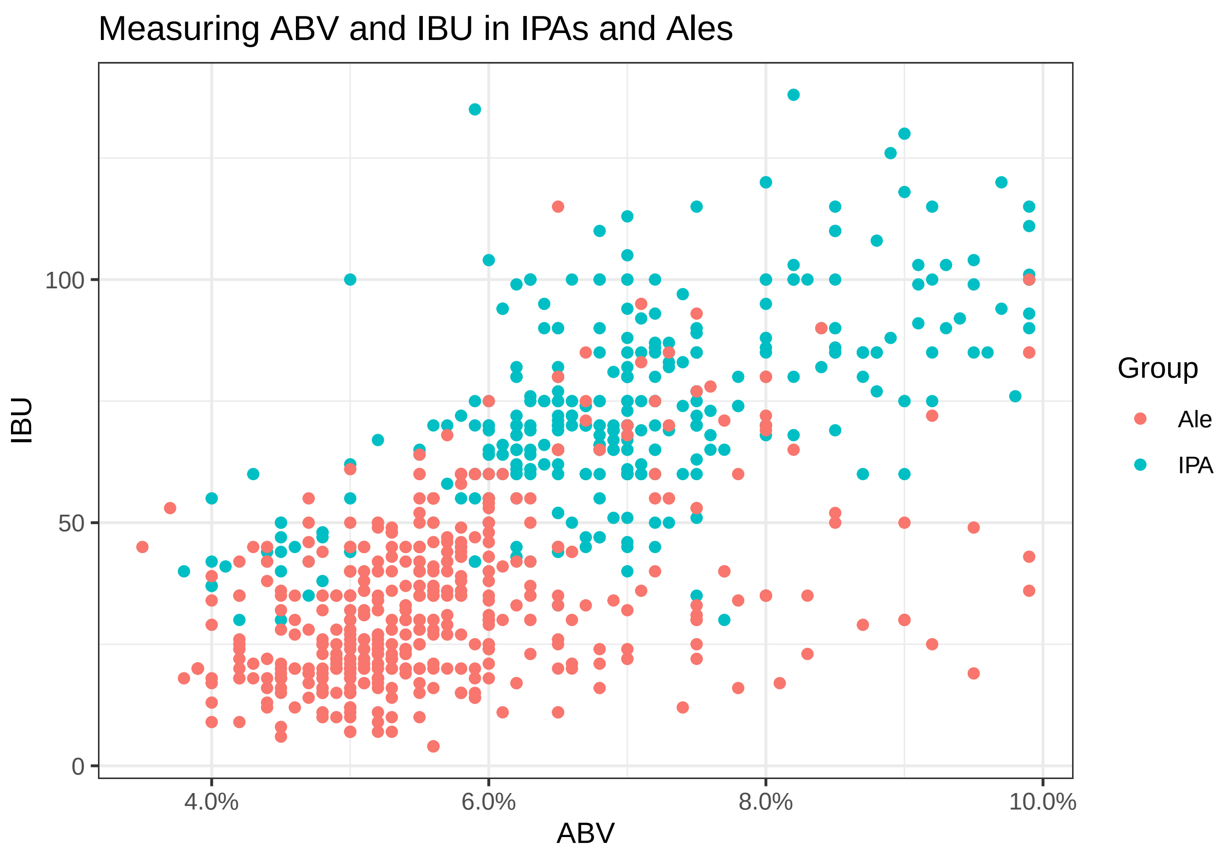
```
sum(grepl("(India | IPA)", join$Style))
```

```
## [1] 395
```

```
IPAs <- join %>% filter(grepl("(India | IPA)", Style)) %>% filter(!grepl("Lager", Style))
Ales <- join %>% filter(grepl("Ale", Style)) %>% filter(!grepl("(India | IPA)", Style))

x <- data.frame(Group = "Ale", c(1:552)) %>% select(Group)
final_Ales <- cbind(x, Ales)

y <- data.frame(Group = "IPA", c(1:392)) %>% select(Group)
final_IPAs <- cbind(y, IPAs)

IPA_Ales <- full_join(final_IPAs, final_Ales)
```

```
## Joining, by = c("Group", "Brewery", "City", "State", "Brewery_id", "Name", "Beer_ID", "ABV", "IBU",
```

```
# We plot the data to get visually acquainted and double check the data. All looks well, moving on.
IPA_Ales %>% ggplot(aes(x = ABV, y = IBU, color = Group)) +
  geom_point() +
  scale_x_continuous(labels = scales::percent) +
  theme_bw() +
  ggtitle("Measuring ABV and IBU in IPAs and Ales")
```

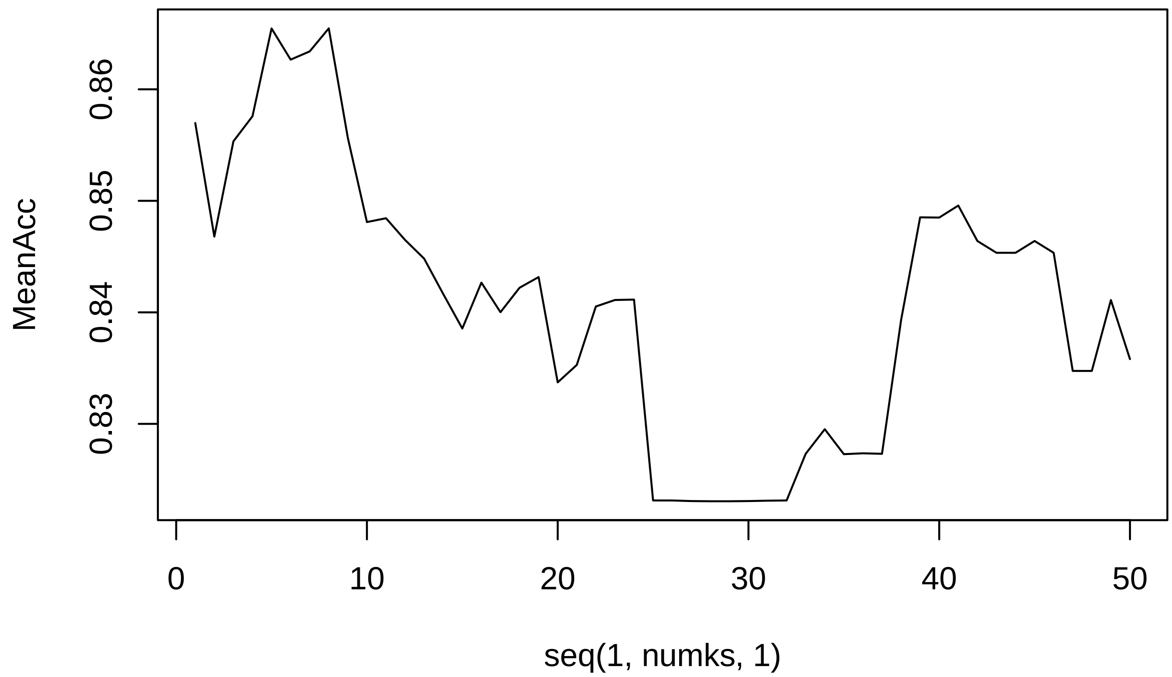



```r
# knn model. We first run a simple internal validation model to determine the accuracy of the model wit

confusionMatrix(table(knn.cv(IPA_Ales[,8:9], IPA_Ales$Group, k = 3), IPA_Ales$Group))
```

```
## Confusion Matrix and Statistics
##
##
##       Ale IPA
##   Ale 486  70
##   IPA  66 322
##
##                Accuracy : 0.8559
##                  95% CI : (0.8319, 0.8777)
##     No Information Rate : 0.5847
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.7029
##
##  Mcnemar's Test P-Value : 0.797
##
##             Sensitivity : 0.8804
##             Specificity : 0.8214
##          Pos Pred Value : 0.8741
##          Neg Pred Value : 0.8299
##              Prevalence : 0.5847
##          Detection Rate : 0.5148
```

```
##    Detection Prevalence : 0.5890
##       Balanced Accuracy : 0.8509
##
##        'Positive' Class : Ale
##
```

```r
#We must establish the optimal number for k, with regards to accuracy. This runs all the k's from 1-50 f

set.seed(1)
iterations = 500
numks = 50

masterAcc = matrix(nrow = iterations, ncol = numks)

for(j in 1:iterations)
{

  for(i in 1:numks)
  {
    CM = confusionMatrix(table(IPA_Ales$Group, knn.cv(IPA_Ales[,8:9], IPA_Ales$Group, k = i)))
    masterAcc[j,i] = CM$overall[1]

  }

}

MeanAcc = colMeans(masterAcc)

plot(seq(1,numks,1),MeanAcc, type = "l")
```




```r
which.max(MeanAcc)
```

```
## [1] 8
```

```r
max(MeanAcc)
```

```
## [1] 0.8654661
```

```r
confusionMatrix(table(IPA_Ales$Group, knn.cv(IPA_Ales[,8:9], IPA_Ales$Group, k = 8)))
```

```
## Confusion Matrix and Statistics
##
##
##       Ale IPA
##   Ale 498  54
##   IPA  71 321
##
##                Accuracy : 0.8676
##                  95% CI : (0.8443, 0.8886)
##     No Information Rate : 0.6028
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.7256
##
```

```
##  Mcnemar's Test P-Value : 0.1524
##
##             Sensitivity : 0.8752
##             Specificity : 0.8560
##          Pos Pred Value : 0.9022
##          Neg Pred Value : 0.8189
##              Prevalence : 0.6028
##          Detection Rate : 0.5275
##    Detection Prevalence : 0.5847
##       Balanced Accuracy : 0.8656
##
##        'Positive' Class : Ale
##
```

Although we checked accuracy based on multiple iterations, we report on a single run using a specific seed for reproducibility.

The overall accuracy of our internal KNN classification model was 86.8%.

Given no information and guessing all classifications to be other Ales, accuracy was 60.28%

The sensitivity, or the model's ability to accurately classify other Ales, was 87.5%.

The specificity, or the model's ability to accurately classify IPAs, was 85.6%.

Additional insights from exploring the data.

```r
#Naive Bayes
nbIPA_Ales <- IPA_Ales %>% select(Group, ABV, IBU)
naiveBayes(Group~., data = nbIPA_Ales )
```

We explored the possibility of creating a Naive Bayes model which predicts the preference of a state for IPAs or Ales.

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##       Ale       IPA
## 0.5847458 0.4152542
##
## Conditional probabilities:
##      ABV
```

```
## Y           [,1]       [,2]
##   Ale 0.05655616 0.01112430
##   IPA 0.06914286 0.01216069
##
##      IBU
## Y         [,1]     [,2]
##   Ale 34.33333 17.97471
##   IPA 71.94898 19.54567
```

```r
iterations = 100
masterAcc = matrix(nrow = iterations)
splitPerc = .8 #Training / Test split Percentage
for(j in 1:iterations)
{
  trainIndices = sample(1:dim(nbIPA_Ales)[1],round(splitPerc * dim(nbIPA_Ales)[1]))
  train = nbIPA_Ales[trainIndices,]
  test = nbIPA_Ales[-trainIndices,]
  model = naiveBayes(train[,2:3],train$Group)
  table(test$Group,predict(model,test[,2:3]))
  CM = confusionMatrix(table(test$Group,predict(model,test[,2:3])))
  masterAcc[j] = CM$overall[1]
}
MeanAcc = colMeans(masterAcc)
MeanAcc
```

```
## [1] 0.8419577
```

The model was able to predict IPA:Ale classification based on ABV and IBU inputs.

```r
### t-test
Ales_ABV <- final_Ales %>% select(ABV, Group)
IPAs_ABV <- final_IPAs %>% filter(!grepl("Lager", Style)) %>% select(ABV, Group)

ABVjoin <- full_join(Ales_ABV, IPAs_ABV)
```

Next, we run a simple independent sample Welch's t-test for both ABV and IBU to determine if there's a significant difference between the groups in those metrics.

```
## Joining, by = c("ABV", "Group")
```

```r
t.test(log(ABV) ~ Group, data = ABVjoin)
```

```
##
##  Welch Two Sample t-test
##
## data:  log(ABV) by Group
## t = -16.91, df = 849.95, p-value < 2.2e-16
## alternative hypothesis: true difference in means between group Ale and group IPA is not equal to 0
## 95 percent confidence interval:
```

```
##  -0.2260548 -0.1790364
## sample estimates:
## mean in group Ale mean in group IPA
##         -2.889941         -2.687395
```

```
t.test(IBU ~ Group, data = IPA_Ales)
```

```
##
##  Welch Two Sample t-test
##
## data:  IBU by Group
## t = -30.118, df = 797.55, p-value < 2.2e-16
## alternative hypothesis: true difference in means between group Ale and group IPA is not equal to 0
## 95 percent confidence interval:
##  -40.06727 -35.16402
## sample estimates:
## mean in group Ale mean in group IPA
##          34.33333          71.94898
```

In both t-tests the p-values were found to be <.0001, providing overwhelming evidence that the IPA group and the Ales group are not equal to each other in either ABV and IBU.

```
##For this NB model, we are able to predict IPA:Ale preference, by simply including a state as an input

nb2 <- IPA_Ales %>% select(State, Group) %>% mutate(State = as.factor(State))
model <- naiveBayes(Group~., data = nb2)
predict(model, data.frame(State = "NH"), type = 'raw')
```

Here, we apply the same logic as the previous NB model.

```
##            Ale       IPA
## [1,] 0.3556701 0.6443299
```

```
###For this next NB model, we would like to extend the scope and predict preference of style of beer (a
df <- join %>% select(Style, City, State)
model <- naiveBayes(Style~., data = df)
predict(model, data.frame(State = "CO", City = "Buena Vista"))
```

```
## [1] American IPA
## 90 Levels: Abbey Single Ale Altbier ... Witbier
```

```
###For this NB model, we do the same as the one above, predicting style, except only using State as inp
df2 <- df %>% select(Style, State)
model <- naiveBayes(Style~State, data = df2)
predict(model, data.frame(State = "CO"))
```

```
## [1] American Pale Ale (APA)
## 90 Levels: Abbey Single Ale Altbier ... Witbier
```

```r
### For this NB model, we would like to predict which city would a particular style of beer be most wel

df1 <- df %>% select(Style, City)
model <- naiveBayes(City~Style, data = df1)
pred <- predict(model, df1$Style)
CM <- confusionMatrix(as.factor(pred), as.factor(df1$City))
predict(model, data.frame(Style = "American IPA"))
```

```
## [1] San Diego
## 281 Levels: Abingdon Abita Springs Afton Albuquerque Anchorage ... York
```

```r
###This last NB similarly uses a Style of beer and predicts the State it would be most popular.

model <- naiveBayes(State~Style, data = df2)
pred <- predict(model, df2$Style)
CM <- confusionMatrix(as.factor(pred), as.factor(df2$State))
predict(model, data.frame(Style = "American IPA"))
```

```
## [1] CA
## 50 Levels: AK AL AR AZ CA CO CT DC DE FL GA HI IA ID IL IN KS KY LA MA ... WY
```

These Naive-Bayes models give us a lot to work with when it comes to marketing research and discovering geographic patterns for the data.

We came across a website that was using ratings of beer to create a table for top rated beer per state and decided to clean up and provide a geographic visualization of each respective state's highest-rated beer. Please see tableau visualizations.

```r
# Scraping website for Top Rated Beers by State data

content <- read_html("https://vinepair.com/articles/best-highest-rated-beer-every-state/")
tables <- content %>% html_table(fill = TRUE)
first_table <- tables[[1]]
first_table <- first_table[-1,]
topbeer <- first_table %>% rename(State = X1, Beer = X2)
topbeer <- topbeer %>% cbind(data.frame(state = state.abb[match(topbeer$State, state.name)]))
topbeer[is.na(topbeer)] <- "DC"
topbeer <- topbeer %>%
  select(state, Beer) %>%
  rename(State = state) %>%
  separate(Beer, into = c("Name", "Brewery", "Style"), sep = "\n") %>%
  separate(Style, into = c("Style", "ABV"), sep = "([|])")
```

```
## Warning: Expected 2 pieces. Missing pieces filled with `NA` in 1 rows [39].
```

```r
head(topbeer)
```

```
##   State                         Name                       Brewery
## 1    AL                     El Gordo   Good People Brewing Company
```

```
## 2    AK                        Blessed     Anchorage Brewing Company
## 3    AZ White Russian Imperial Stout            Sun Up Brewing Co.
## 4    AR                           BDCS                Ozark Beer Co.
## 5    CA            Pliny The Younger Russian River Brewing Company
## 6    CO         Medianoche - Coconut         WeldWerks Brewing Co.
##                        Style     ABV
## 1  Stout - Russian Imperial   13.90%
## 2 Stout - American Imperial   14.00%
## 3 Stout - American Imperial    9.20%
## 4 Stout - American Imperial   10.20%
## 5            IPA - Imperial   10.25%
## 6 Stout - American Imperial   14.10%
```

```
#Tableau Workbook URL: https://public.tableau.com/shared/4QFJCDFGZ?:display_count=n&:origin=viz_share_l
```