Final

Jiang

2022-12-12

```
library(tidytuesdayR)
library(ggplot2)
library(dplyr)
```

Package

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(magrittr)
library(tidyr)
```

```
##
## Attaching package: 'tidyr'

## The following object is masked from 'package:magrittr':
##
##     extract
```

```
library(tidyselect)
library(purrr)
```

```
##
## Attaching package: 'purrr'

## The following object is masked from 'package:magrittr':
##
##     set_names
```

```r
library(tibble)
library(readr)
library(stringr)
#install.packages('janitor')
library(viridis)
```

```
## Loading required package: viridisLite
```

```r
library(janitor)
```

```
##
## Attaching package: 'janitor'

## The following objects are masked from 'package:stats':
##
##     chisq.test, fisher.test
```

```r
library(DT)
library(kableExtra)
```

```
## Warning in !is.null(rmarkdown::metadata$output) && rmarkdown::metadata$output
## %in% : 'length(x) = 3 > 1' in coercion to 'logical(1)'

##
## Attaching package: 'kableExtra'

## The following object is masked from 'package:dplyr':
##
##     group_rows
```

```r
library(tinytex)
#install.packages("webshot")
#webshot::install_phantomjs()
```

```r
raw_dat <- tidytuesdayR::tt_load('2022-01-18')
```

```
## --- Compiling #TidyTuesday Information for 2022-01-18 ----

## --- There is 1 file available ---

## --- Starting Download ---

##
##  Downloading file 1 of 1: `chocolate.csv`

## --- Download complete ---
```

```r
dat <- raw_dat$chocolate
glimpse(dat)
```

```
## Rows: 2,530
## Columns: 10
## $ ref                              <dbl> 2454, 2458, 2454, 2542, 2546, 2546, 25~
## $ company_manufacturer             <chr> "5150", "5150", "5150", "5150", "5150"~
## $ company_location                 <chr> "U.S.A.", "U.S.A.", "U.S.A.", "U.S.A."~
## $ review_date                      <dbl> 2019, 2019, 2019, 2021, 2021, 2021, 20~
## $ country_of_bean_origin           <chr> "Tanzania", "Dominican Republic", "Mad~
## $ specific_bean_origin_or_bar_name <chr> "Kokoa Kamili, batch 1", "Zorzal, batc~
## $ cocoa_percent                    <chr> "76%", "76%", "76%", "68%", "72%", "80~
## $ ingredients                      <chr> "3- B,S,C", "3- B,S,C", "3- B,S,C", "3~
## $ most_memorable_characteristics   <chr> "rich cocoa, fatty, bready", "cocoa, v~
## $ rating                           <dbl> 3.25, 3.50, 3.75, 3.00, 3.00, 3.25, 3.~
```

```r
# Remove "%" sign from cocoa content and convert it to a numeric variable
#convert cocoa_percent to a numeric
chocolate <- dat |>
  mutate(cocoa_percent = str_extract(cocoa_percent, "\\d+") |>
  as.numeric())|>
  mutate(country_of_bean_origin=
           recode(country_of_bean_origin,
                  "Congo"= "Republic of Congo",
                  "DR Congo"= "Democratic Republic of the Congo"))
```

```r
chocolate_df<- chocolate |>
   mutate(n_ingredients = str_extract(ingredients, "\\d") |> as.numeric(),
     ingredients_list = str_extract(ingredients, "[A-Za-z,*]+")) |>
  separate_rows(ingredients_list,sep = ",") |>
  mutate(ingredients_list = str_replace_all(ingredients_list,c(
        "^S\\*$" = "sweetener",
        "^S$" = "sugar",
        "C" = "cocoa_butter",
        "V" = "vanilla",
        "B" = "beans",
        "L" = "lecithin",
        "^Sa$" = "salt")),
    ingredients_list = replace_na(ingredients_list, "unknown"),
    flag = 1) |>
  pivot_wider(names_from = ingredients_list,values_from = flag,
              values_fill = 0)
```

Data preprocess and Exploratory Data Analysis

```r
# Create an object with total number of chocolate counts per company location
Country_Counts <- chocolate |>
  select(company_manufacturer,company_location) |>
  group_by(company_location) |>
  summarise(Count = n()) |>
  arrange(desc(Count)) # Arranges total counts from highest to lowest

# Create table
datatable(Country_Counts, colnames = c("Company Location", "Count"))
```

Company Location	Count

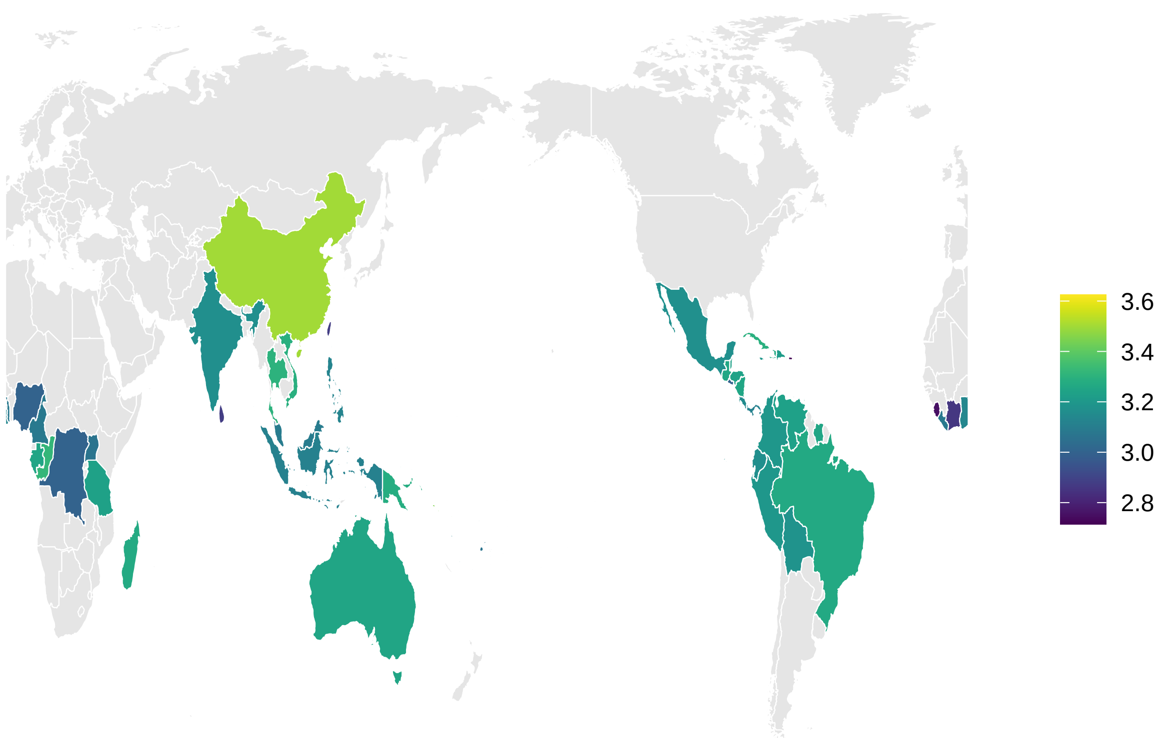
Company location

```r
#summarise by country
chocolate_df2 <- chocolate_df |>
  group_by(country = country_of_bean_origin)|>
  summarise(avg_rating=mean(na.omit(rating)),
            avg_cocoa=mean(na.omit(cocoa_percent)))

#retrieve country geo data
world <- map_data("world2")|>
  filter(region != "Antarctica")

world |>
```

```r
merge(chocolate_df2, by.x = "region", by.y = "country", all.x = T) %>%
arrange(group, order) %>%
ggplot(aes(x = long, y = lat, group = group, fill = avg_rating)) +
geom_polygon(color = "white", size = 0.2) +
scale_fill_viridis("", na.value = "gray90") +
theme_minimal() +
theme(axis.text = element_blank(),
      axis.title = element_blank(),
      panel.grid = element_blank())
```

Worldmap of country of bean origin

```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use `linewidth` instead.
```

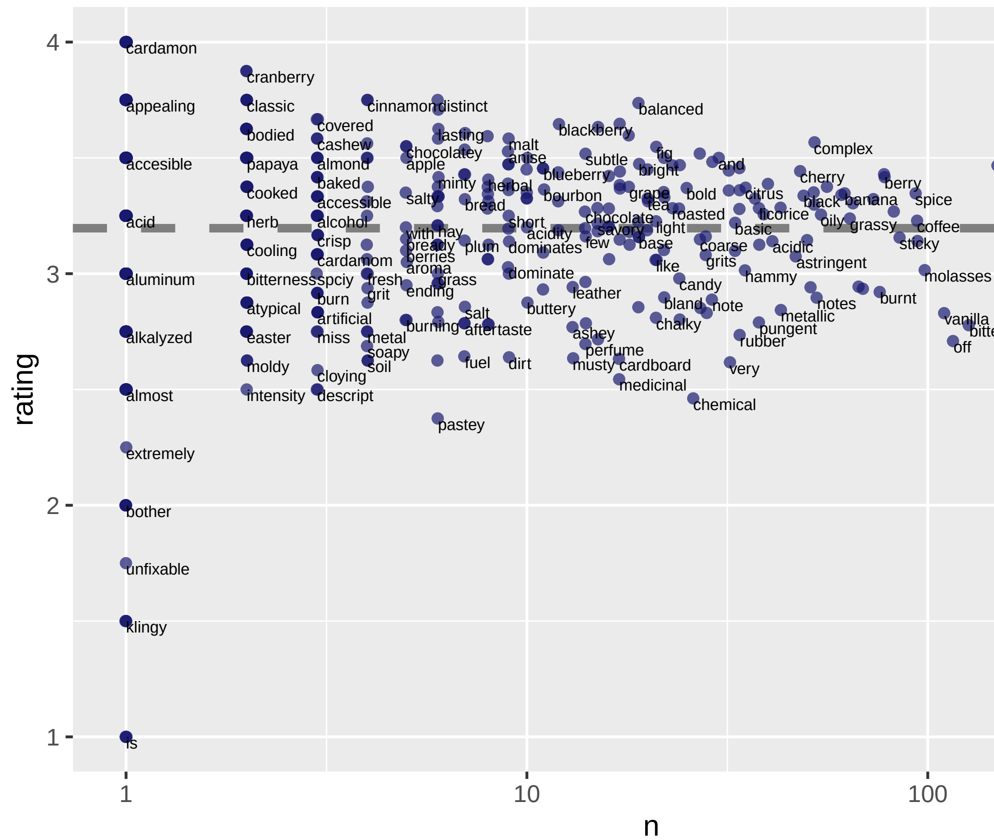



```r
ggsave("featured.png")
```

```
## Saving 6.5 x 4.5 in image
```

```r
library(tidytext)
```

```r
tidy_chocolate <- chocolate_df |>
  unnest_tokens(word, most_memorable_characteristics)

tidy_chocolate |>
  group_by(word) |>
  summarise(n = n(),rating = mean(rating)) |>
  ggplot(aes(n, rating)) +
  geom_hline( yintercept = mean(chocolate$rating), lty = 2,
              color = "gray50", size = 1.5 ) +
  geom_jitter(color = "midnightblue", alpha = 0.7) +
  geom_text(aes(label = word),
    check_overlap = TRUE,
    vjust = "top", hjust = "left",size = 2) +
  scale_x_log10()
```



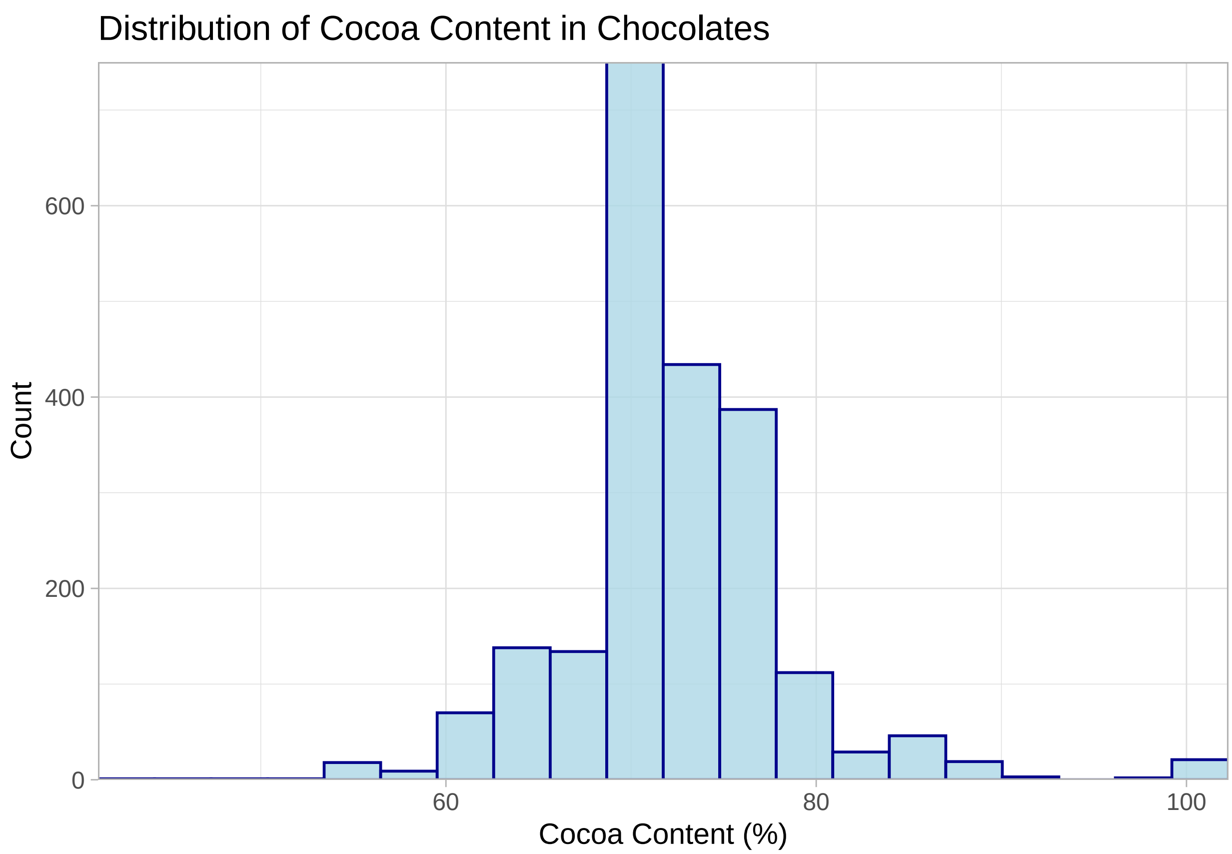
most memorable characteristics

```r
summary(chocolate_df$cocoa_percent)
```

Cocoa content

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   42.00   70.00   70.00   71.64   74.00  100.00
```

```r
# Histogram of Cocoa Content
ggplot(data = chocolate_df, aes(x = cocoa_percent)) +
  geom_histogram(bins = 20, alpha = 0.80, color = "dark blue", fill = 'light blue') +
  theme_light() +
  coord_cartesian(expand = FALSE, ylim = c(0, 750)) +
  labs(x = "Cocoa Content (%)",
       y = "Count",
       title = "Distribution of Cocoa Content in Chocolates")
```



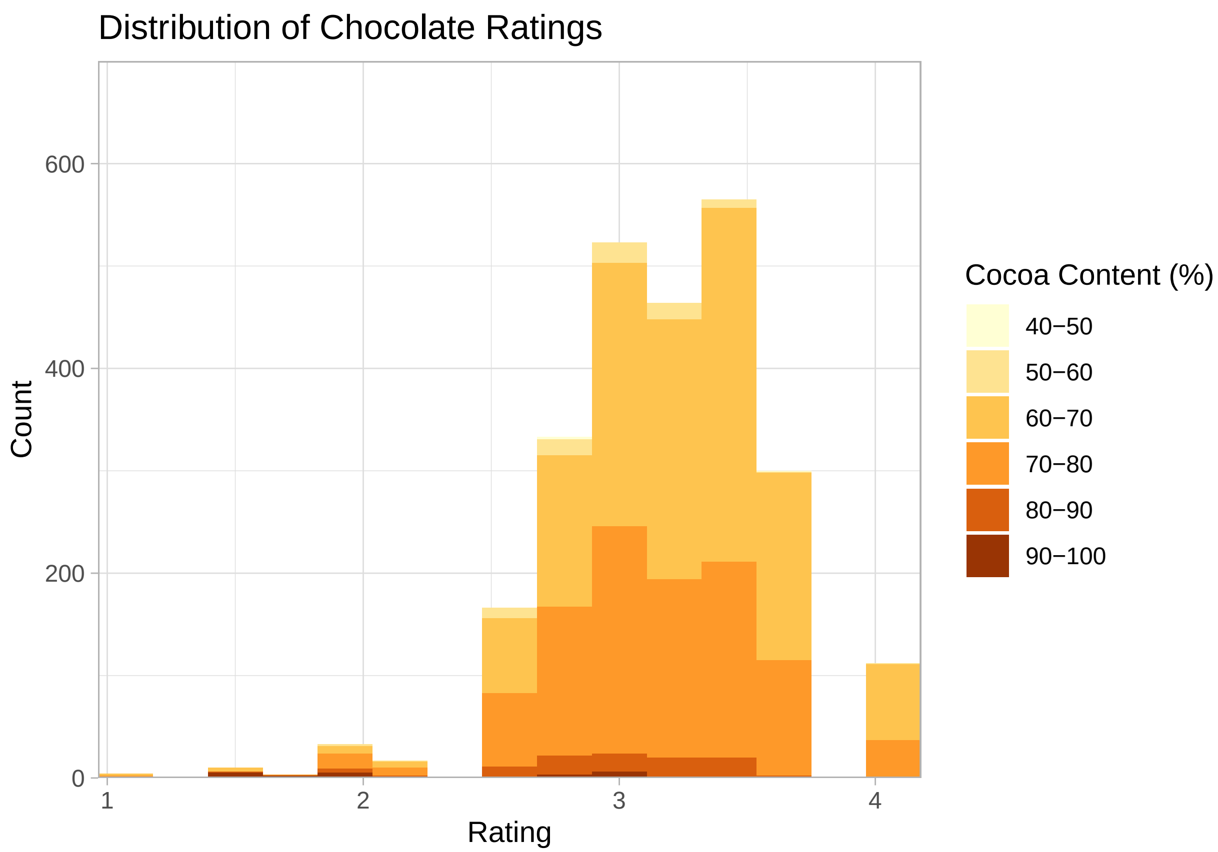

```r
summary(chocolate_df$rating)
```

Rating

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   3.000   3.250   3.196   3.500   4.000
```

```r
# Histogram of Chocolate Ratings by Cocoa Content
# Create bins of various ranges of cocoa content
chocolate_df$Cocoa.Percent_bin <- cut(chocolate_df$cocoa_percent,
                                      breaks = c(40, 50, 60, 70, 80, 90,100))
# plot
ggplot(data = chocolate_df, aes(x = rating, fill = Cocoa.Percent_bin)) +
```

```r
  geom_histogram(bins = 15) +
  theme_light() +
  coord_cartesian(expand = FALSE, ylim = c(0, 700)) +
  scale_fill_brewer(type = "seq",
                    palette = "YlOrBr",
                    labels = c("40-50", "50-60", "60-70", "70-80", "80-90", "90-100"),
                    name = "Cocoa Content (%)") +
  labs(x = "Rating",
       y = "Count",
       title = "Distribution of Chocolate Ratings")
```




```r
library(caret)
```

Data partitioning

```
## Loading required package: lattice

##
## Attaching package: 'caret'

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

```r
#library(matrixStats)
```

```r
set.seed(123)
#we use a training data set containing a random sample of 70% of the observation to perform with "Diabe

partition <- caret::createDataPartition(y = chocolate_df$rating, times = 1, p = 0.7, list = FALSE)

# create training data set
train_set <- chocolate_df[partition,]

# create testing data set, subtracting the rows partition to get remaining 30% of the data
test_set <- chocolate_df[-partition,]
#str(train_set)
#str(test_set)
```

```r
X<-train_set[,c(7,12:17,19)]
y <- train_set$rating
x <- data.matrix(X)
```

```r
x_test <- data.matrix(test_set[,c(7,12:17,19)])
y_test <- test_set$rating
```

```r
RMSE <- function(true_ratings, predicted_ratings){
    sqrt(mean((true_ratings - predicted_ratings)^2))}
```

RMSE

```r
mu <- mean(y, na.rm = TRUE)
mu
```

avg

```
## [1] 3.2022
```

```r
naive_rmse <- RMSE(test_set$rating, mu)
naive_rmse
```

```
## [1] 0.4611441
```

correlation b/w variables

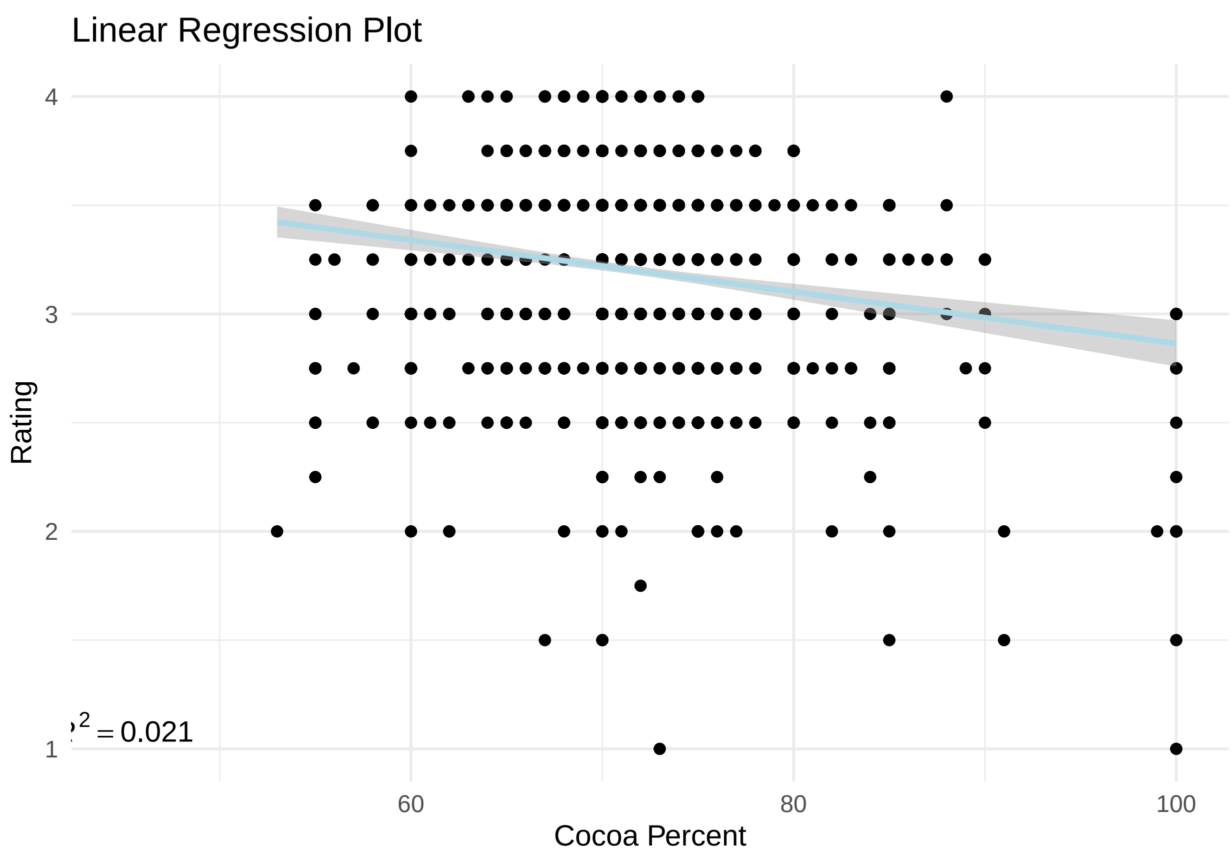
```
# Determine the correlation between cocoa content and chocolate rating
cor(x = train_set$cocoa_percent, y = train_set$rating, method = "pearson")
```

linear model

```
## [1] -0.1491909
```

```
#simple plot of rating vs cocoa%
graph <- ggplot(train_set, aes(x = cocoa_percent, y = rating)) +
  geom_point() +
  geom_smooth(method = "lm", col = "light blue")+
  labs(x='Cocoa Percent', y='Rating', title='Linear Regression Plot') +
  theme(plot.title = element_text(hjust=0.5, size=20, face='bold'))+
  theme_minimal()+
  annotate("text", x = 45, y = 1.1, label = "italic(R) ^ 2 == 0.021", parse= TRUE)

graph
```

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




```
# Fit a linear model to predict rating based on Cocoa Content
mod1 <- lm(rating ~ cocoa_percent, data = train_set)
summary(mod1)
```

```
##
## Call:
## lm(formula = rating ~ cocoa_percent, data = train_set)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.1852 -0.2333  0.0291  0.2791  0.9930
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)    4.052583   0.134325  30.170  < 2e-16 ***
## cocoa_percent -0.011881   0.001871  -6.349 2.74e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4337 on 1771 degrees of freedom
## Multiple R-squared:  0.02226,    Adjusted R-squared:  0.02171
## F-statistic: 40.32 on 1 and 1771 DF,  p-value: 2.738e-10
```

```
mod1$coef
```

```
##   (Intercept) cocoa_percent
##    4.05258267   -0.01188124
```

```
y_hat <- mod1$coef[1] + mod1$coef[2]*test_set$cocoa_percent
sqrt(mean((y_hat - test_set$rating)^2))
```

```
## [1] 0.4565446
```

```
#rmse = 0.4565
```

```
# Fit a linear model to predict rating based on cocoa content and other ingredients
mod2 <- lm(rating ~
                cocoa_percent+
                sweetener+
                sugar+
                cocoa_butter+
                vanilla+
                beans+
                lecithin+
                salt,
              data=train_set)
summary(mod2)
```

correlation between rating and cocoa content, as well as other ingredients

```
##
## Call:
## lm(formula = rating ~ cocoa_percent + sweetener + sugar + cocoa_butter +
```

```
##     vanilla + beans + lecithin + salt, data = train_set)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.98818 -0.27412  0.00096  0.26301  1.03528
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)    3.842284   0.152188  25.247  < 2e-16 ***
## cocoa_percent -0.012537   0.001924  -6.516 9.38e-11 ***
## sweetener     -0.139297   0.206298  -0.675   0.4996
## sugar          0.030761   0.197372   0.156   0.8762
## cocoa_butter   0.039073   0.023540   1.660   0.0971 .
## vanilla       -0.223735   0.032514  -6.881 8.22e-12 ***
## beans          0.253559   0.203363   1.247   0.2126
## lecithin      -0.038591   0.029001  -1.331   0.1835
## salt          -0.065086   0.087647  -0.743   0.4578
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4231 on 1764 degrees of freedom
## Multiple R-squared:  0.0729, Adjusted R-squared:  0.06869
## F-statistic: 17.34 on 8 and 1764 DF,  p-value: < 2.2e-16
```

```
#stemMod2 <- step(mod2,direction = c("both"))
```

```
library(car)
```

```
## Loading required package: carData
```

```
##
## Attaching package: 'car'
```

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

```
## The following object is masked from 'package:dplyr':
##
##     recode
```

```
vif_values <- vif(mod2)
vif_values
```

```
## cocoa_percent     sweetener         sugar  cocoa_butter       vanilla
##      1.110422     12.446042     24.155985      1.231621      1.208095
##         beans      lecithin          salt
##     13.391249      1.264674      1.182485
```

```r
df_vif <- data.frame("Model" = c("cocoa_percent", "sweetener","sugar","cocoa_butter","vanilla","beans",
                 "VIF" = c("1.110422", "12.446042","24.155985","1.231621","1.208095","13.391249","1.264

kbl(df_vif, booktabs = T) |>
  kable_classic(full_width = T, html_font = "Cambria")
```

Model	VIF
cocoa_percent	1.110422
sweetener	12.446042
sugar	24.155985
cocoa_butter	1.231621
vanilla	1.208095
beans	13.391249
lecithin	1.264674
salt	1.182485

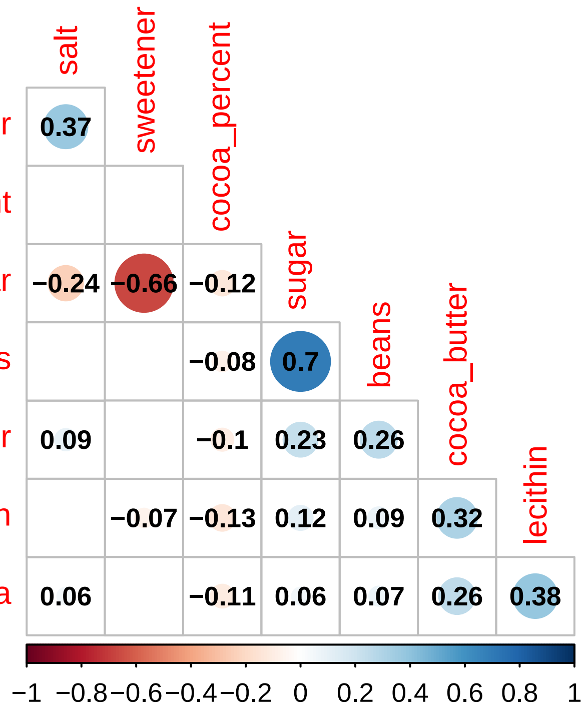
```r
knitr::kable(df_vif, align = "lcc")
```

Model	VIF
cocoa_percent	1.110422
sweetener	12.446042
sugar	24.155985
cocoa_butter	1.231621
vanilla	1.208095
beans	13.391249
lecithin	1.264674
salt	1.182485

```r
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```r
cor1 = cor(X)
testRes = cor.mtest(X, conf.level = 0.95)
corrplot(cor1, p.mat = testRes$p, method = 'circle', type = 'lower', insig='blank',
         addCoef.col ='black', number.cex = 0.8, order = 'AOE', diag=FALSE)
```



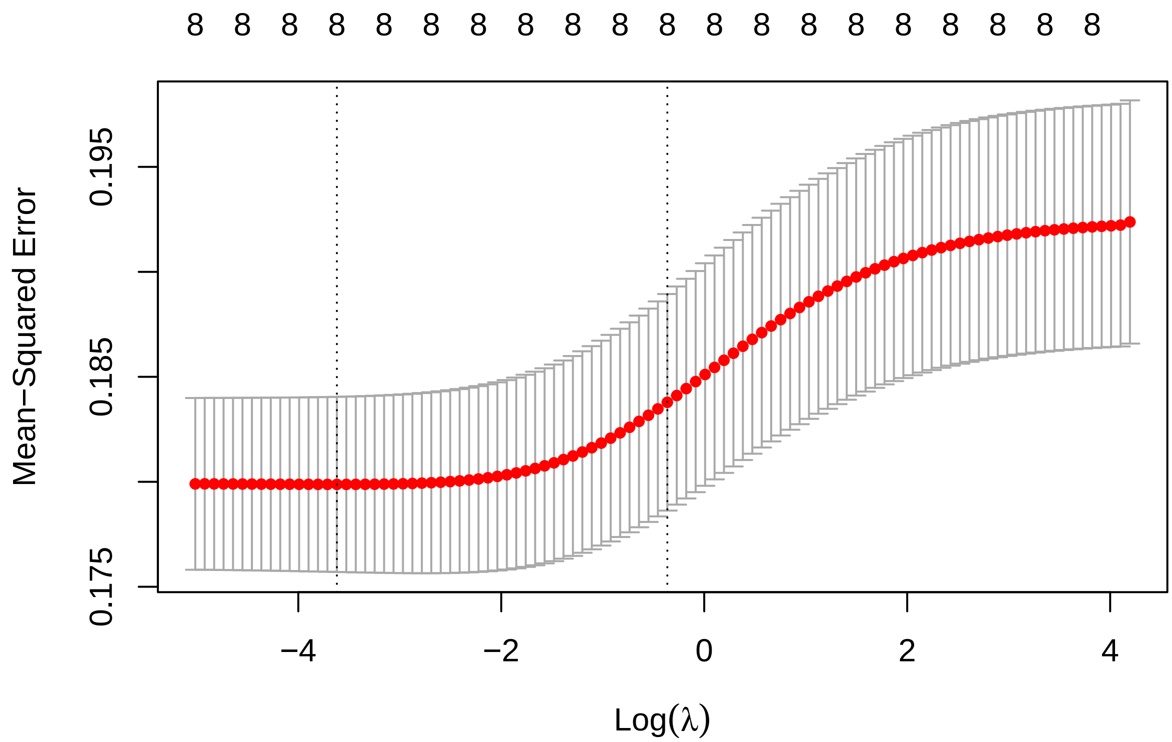

```
library(glmnet)
```

```
## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack

## Loaded glmnet 4.1-6
```

```
mod_ridge <- glmnet(x, y, alpha = 0)
#summary(mod_ridge)
cv_model <- cv.glmnet(x, y, alpha = 0)
best_lambda <- cv_model$lambda.min
best_lambda
```

```
## [1] 0.02679121
```

```
plot(cv_model)
```




```r
best_model <- glmnet(x, y, alpha = 0, lambda = best_lambda)
coef(best_model)
```

```
## 9 x 1 sparse Matrix of class "dgCMatrix"
##                        s0
## (Intercept)     3.78383504
## cocoa_percent -0.01160390
## beans          0.18073901
## sugar          0.09528551
## cocoa_butter   0.03543919
## lecithin      -0.03805942
## vanilla       -0.20827431
## salt          -0.06308000
## sweetener     -0.07147086
```

```r
y_predicted <- predict(mod_ridge, s = best_lambda, newx = x)
sst <- sum((y - mean(y))^2)
sse <- sum((y_predicted - y)^2)
rsq <- 1 - sse/sst
rsq
```

```
## [1] 0.07260188
```

```r
# 0.07255
summary(mod2)
```

```
##
## Call:
## lm(formula = rating ~ cocoa_percent + sweetener + sugar + cocoa_butter +
##     vanilla + beans + lecithin + salt, data = train_set)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.98818 -0.27412  0.00096  0.26301  1.03528
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)    3.842284   0.152188  25.247  < 2e-16 ***
## cocoa_percent -0.012537   0.001924  -6.516 9.38e-11 ***
## sweetener     -0.139297   0.206298  -0.675   0.4996
## sugar          0.030761   0.197372   0.156   0.8762
## cocoa_butter   0.039073   0.023540   1.660   0.0971 .
## vanilla       -0.223735   0.032514  -6.881 8.22e-12 ***
## beans          0.253559   0.203363   1.247   0.2126
## lecithin      -0.038591   0.029001  -1.331   0.1835
## salt          -0.065086   0.087647  -0.743   0.4578
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4231 on 1764 degrees of freedom
## Multiple R-squared:  0.0729, Adjusted R-squared:  0.06869
## F-statistic: 17.34 on 8 and 1764 DF,  p-value: < 2.2e-16
```

```r
# R2 = 0.06869
```

```r
test_set$pred_lm <- predict(best_model, x_test)
# Calculate the RMSE of the predictions
test_set |>
  summarize(rmse = RMSE(rating, pred_lm)) |>
  pull(rmse)
```

```
## [1] 0.437643
```

```r
#rmse = 0.4378
```

```r
library(randomForest)
```

random forest

```
## randomForest 4.7-1.1
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
##
## Attaching package: 'randomForest'

## The following object is masked from 'package:dplyr':
##
##     combine

## The following object is masked from 'package:ggplot2':
##
##     margin
```

```r
set.seed(123)
control <- trainControl(method="cv", number = 5)
grid <- data.frame(mtry = c(1, 5, 10, 25, 50, 100))

train_rf <-  train(x, y,
                   method = "rf",
                   ntree = 150,
                   trControl = control,
                   tuneGrid = grid,
                   nSamp = 5000)
```

```
## Warning in randomForest.default(x, y, mtry = param$mtry, ...): invalid mtry:
## reset to within valid range

## Warning in randomForest.default(x, y, mtry = param$mtry, ...): invalid mtry:
## reset to within valid range

## Warning in randomForest.default(x, y, mtry = param$mtry, ...): invalid mtry:
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## reset to within valid range

## Warning in randomForest.default(x, y, mtry = param$mtry, ...): invalid mtry:
## reset to within valid range

## Warning in randomForest.default(x, y, mtry = param$mtry, ...): invalid mtry:
```
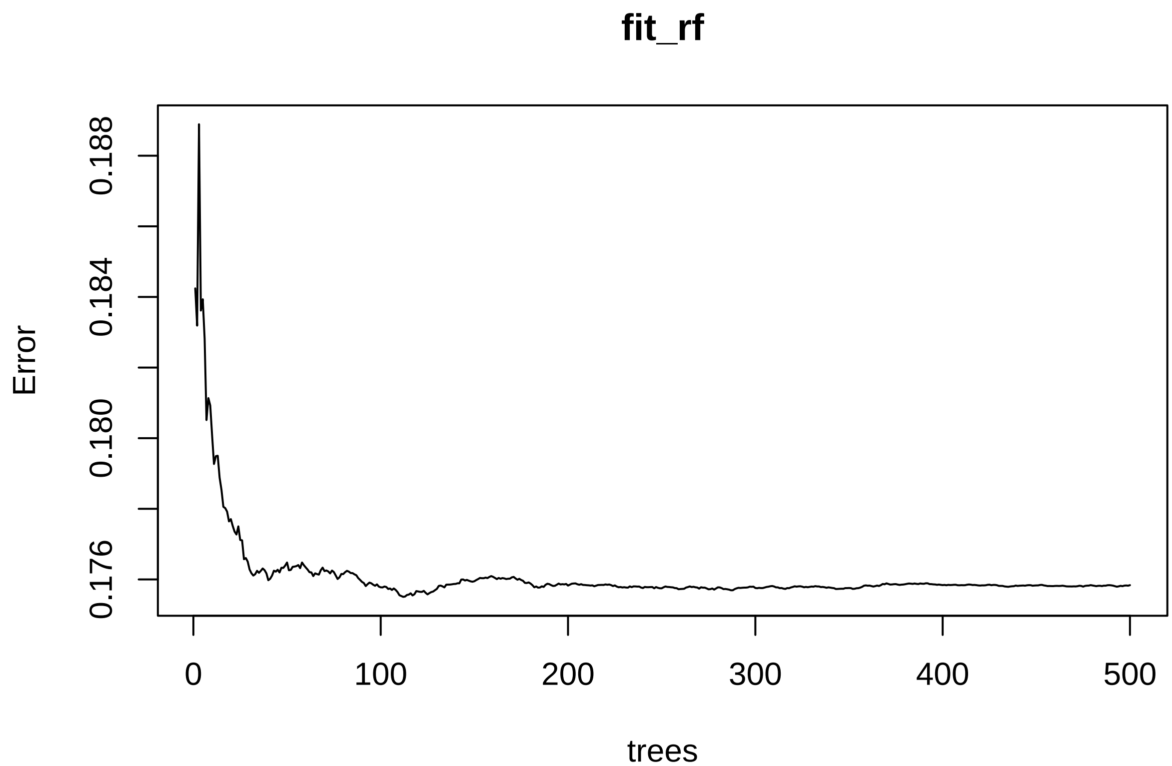

```
## reset to within valid range

## Warning in randomForest.default(x, y, mtry = param$mtry, ...): invalid mtry:
## reset to within valid range

## Warning in randomForest.default(x, y, mtry = param$mtry, ...): invalid mtry:
## reset to within valid range

## Warning in randomForest.default(x, y, mtry = param$mtry, ...): invalid mtry:
## reset to within valid range

## Warning in randomForest.default(x, y, mtry = param$mtry, ...): invalid mtry:
## reset to within valid range

## Warning in randomForest.default(x, y, mtry = param$mtry, ...): invalid mtry:
## reset to within valid range

## Warning in randomForest.default(x, y, mtry = param$mtry, ...): invalid mtry:
## reset to within valid range

## Warning in randomForest.default(x, y, mtry = param$mtry, ...): invalid mtry:
## reset to within valid range

## Warning in randomForest.default(x, y, mtry = param$mtry, ...): invalid mtry:
## reset to within valid range

## Warning in randomForest.default(x, y, mtry = param$mtry, ...): invalid mtry:
## reset to within valid range
```

```
fit_rf <- randomForest(x, y, mtry = train_rf$bestTune$mtry)
plot(fit_rf)
```




```r
# Create a column called pred to store the prediction from the random forest model
test_set$pred_rf <- predict(fit_rf, x_test)

# Calculate the RMSE of the predictions
test_set |>
  summarize(rmse = RMSE(rating, pred_rf)) |>
  pull(rmse)
```

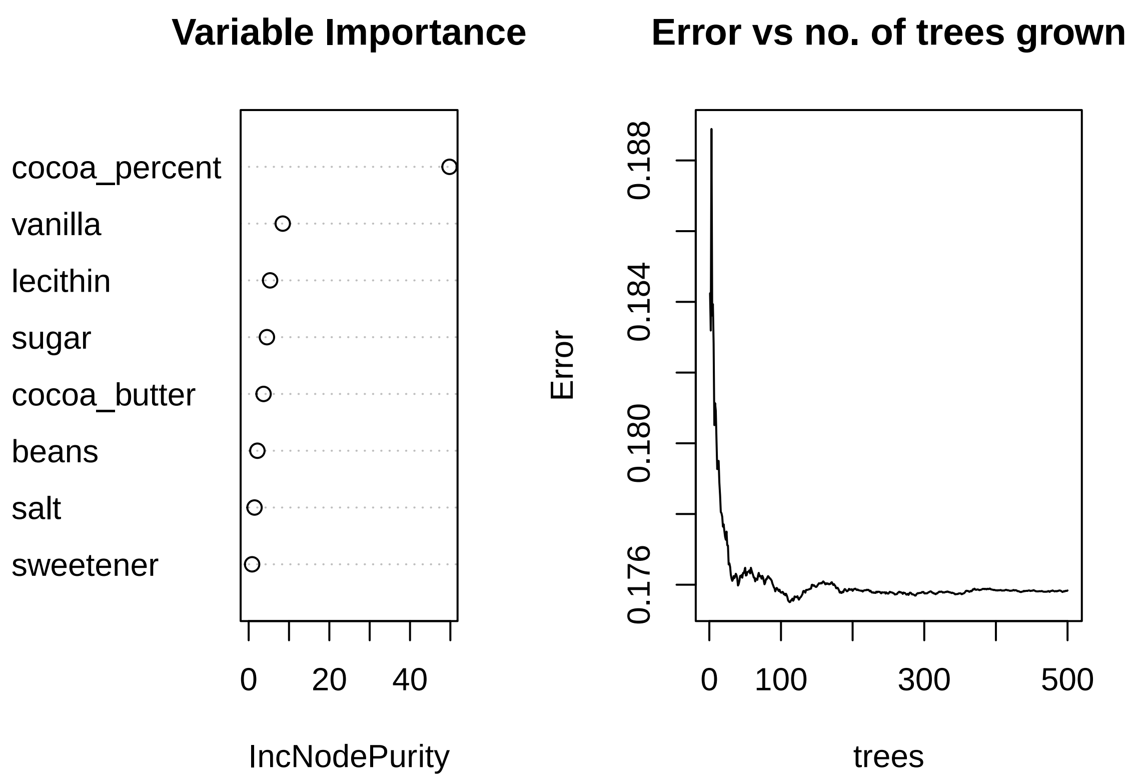
```
## [1] 0.4330936
```

```r
# 0.4331
```

```r
importance(fit_rf)
```

```
##               IncNodePurity
## cocoa_percent    49.7922810
## beans             2.1618308
## sugar             4.5233638
## cocoa_butter      3.6928937
## lecithin          5.3122769
## vanilla           8.4428939
## salt              1.4504728
## sweetener         0.8551413
```

```r
par(mfrow = c(1, 2))
varImpPlot(fit_rf, type = 2, main = "Variable Importance",col = 'black')
plot(fit_rf, main = "Error vs no. of trees grown")
```




```r
#install.packages("kknn")
library(kknn)
```

knn

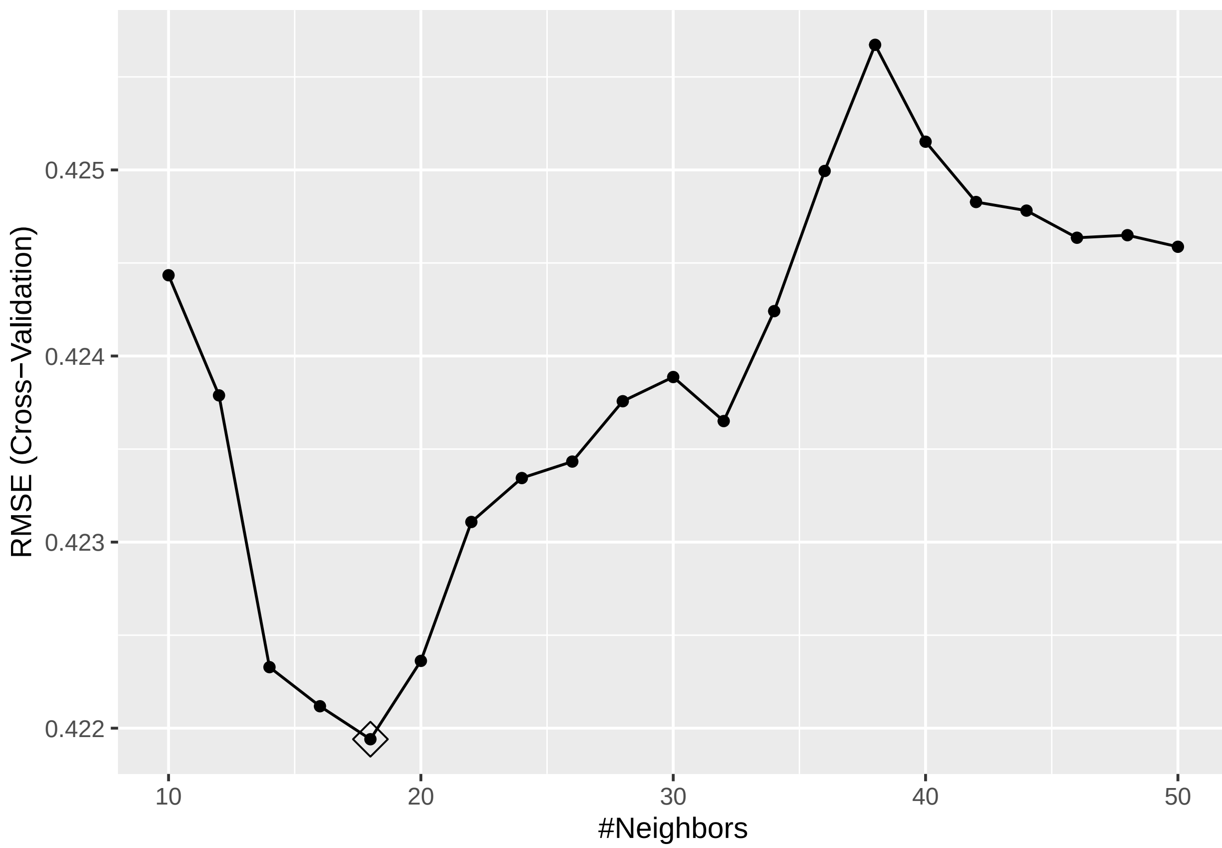
```
##
## Attaching package: 'kknn'

## The following object is masked from 'package:caret':
##
##     contr.dummy
```

```r
grid1 = expand.grid(.k=seq(10,50, by=2))
control = trainControl(method="cv")
set.seed(123)

fit_knn = train(rating~cocoa_percent+
```

```r
                 sweetener+
                 sugar+
                 cocoa_butter+
                 vanilla+
                 beans+
                 lecithin+
                 salt, data=train_set, method="knn",
                 trControl=control, tuneGrid=grid1,na.action = na.omit)
fit_knn
```

```
## k-Nearest Neighbors
##
## 1773 samples
##    8 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 1595, 1596, 1596, 1597, 1595, 1597, ...
## Resampling results across tuning parameters:
##
##   k   RMSE       Rsquared    MAE
##   10  0.4244341  0.06951304  0.3417561
##   12  0.4237884  0.07229677  0.3411259
##   14  0.4223281  0.07763809  0.3392188
##   16  0.4221180  0.07705565  0.3388540
##   18  0.4219408  0.07701505  0.3385018
##   20  0.4223618  0.07572680  0.3386341
##   22  0.4231081  0.07238649  0.3397018
##   24  0.4233443  0.07033047  0.3395819
##   26  0.4234328  0.07009555  0.3395376
##   28  0.4237570  0.06857316  0.3396764
##   30  0.4238872  0.06773152  0.3395385
##   32  0.4236504  0.06890655  0.3394593
##   34  0.4242412  0.06654936  0.3402759
##   36  0.4249944  0.06304921  0.3408384
##   38  0.4256723  0.06135122  0.3419069
##   40  0.4251516  0.06404765  0.3416541
##   42  0.4248276  0.06572326  0.3412550
##   44  0.4247814  0.06600362  0.3412703
##   46  0.4246355  0.06680723  0.3411919
##   48  0.4246493  0.06670992  0.3412089
##   50  0.4245871  0.06705602  0.3410232
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was k = 18.
```

```r
ggplot(fit_knn, highlight = TRUE)#k = 18
```




```
test_set$pred_knn <- predict(fit_knn, x_test)

# Calculate the RMSE of the predictions
test_set |>
  summarize(rmse = RMSE(rating, pred_knn)) |>
  pull(rmse)
```

```
## [1] 0.4389389
```

```
#0.4399
```

```
df <- data.frame("Model" = c("Just The Average","Simple Linear Regression", "Multivariable Regression",
                 "RMSE" = c("0.4611","0.4565", "0.4378","0.4331","0.4399"))
kbl(df, booktabs = T) |>
  kable_classic(full_width = T, html_font = "Cambria")
```

RMSE result

Model	RMSE
Just The Average	0.4611
Simple Linear Regression	0.4565
Multivariable Regression	0.4378
Random Forest Model	0.4331
K-Nearest Neighbors Model	0.4399

```r
knitr::kable(df, align = "lcc")
```

Model	RMSE
Just The Average	0.4611
Simple Linear Regression	0.4565
Multivariable Regression	0.4378
Random Forest Model	0.4331
K-Nearest Neighbors Model	0.4399

Appendix: All code for this report

```
library(tidytuesdayR)
library(ggplot2)
library(dplyr)
library(magrittr)
library(tidyr)
library(tidyselect)
library(purrr)
library(tibble)
library(readr)
library(stringr)
#install.packages('janitor')
library(viridis)
library(janitor)
library(DT)
library(kableExtra)
library(tinytex)
#install.packages("webshot")
#webshot::install_phantomjs()
raw_dat <- tidytuesdayR::tt_load('2022-01-18')
dat <- raw_dat$chocolate
glimpse(dat)
# Remove "%" sign from cocoa content and convert it to a numeric variable
#convert cocoa_percent to a numeric
chocolate <- dat |>
  mutate(cocoa_percent = str_extract(cocoa_percent, "\\d+") |>
  as.numeric())|>
  mutate(country_of_bean_origin=
         recode(country_of_bean_origin,
                "Congo"= "Republic of Congo",
                "DR Congo"= "Democratic Republic of the Congo"))
chocolate_df<- chocolate |>
   mutate(n_ingredients = str_extract(ingredients, "\\d") |> as.numeric(),
     ingredients_list = str_extract(ingredients, "[A-Za-z,*]+")) |>
  separate_rows(ingredients_list,sep = ",") |>
  mutate(ingredients_list = str_replace_all(ingredients_list,c(
        "^S\\*$" = "sweetener",
        "^S$" = "sugar",
        "C" = "cocoa_butter",
        "V" = "vanilla",
        "B" = "beans",
        "L" = "lecithin",
        "^Sa$" = "salt")),
    ingredients_list = replace_na(ingredients_list, "unknown"),
    flag = 1) |>
  pivot_wider(names_from = ingredients_list,values_from = flag,
              values_fill = 0)
# Create an object with total number of chocolate counts per company location
Country_Counts <- chocolate |>
  select(company_manufacturer,company_location) |>
  group_by(company_location) |>
  summarise(Count = n()) |>
```

```r
  arrange(desc(Count)) # Arranges total counts from highest to lowest

# Create table
datatable(Country_Counts, colnames = c("Company Location", "Count"))
#summarise by country
chocolate_df2 <- chocolate_df |>
  group_by(country = country_of_bean_origin)|>
  summarise(avg_rating=mean(na.omit(rating)),
            avg_cocoa=mean(na.omit(cocoa_percent)))

#retrieve country geo data
world <- map_data("world2")|>
  filter(region != "Antarctica")

world |>
  merge(chocolate_df2, by.x = "region", by.y = "country", all.x = T) %>%
  arrange(group, order) %>%
  ggplot(aes(x = long, y = lat, group = group, fill = avg_rating)) +
  geom_polygon(color = "white", size = 0.2) +
  scale_fill_viridis("", na.value = "gray90") +
  theme_minimal() +
  theme(axis.text = element_blank(),
        axis.title = element_blank(),
        panel.grid = element_blank())
ggsave("featured.png")

library(tidytext)

tidy_chocolate <- chocolate_df |>
  unnest_tokens(word, most_memorable_characteristics)

tidy_chocolate |>
  group_by(word) |>
  summarise(n = n(),rating = mean(rating)) |>
  ggplot(aes(n, rating)) +
  geom_hline( yintercept = mean(chocolate$rating), lty = 2,
              color = "gray50", size = 1.5 ) +
  geom_jitter(color = "midnightblue", alpha = 0.7) +
  geom_text(aes(label = word),
    check_overlap = TRUE,
    vjust = "top", hjust = "left",size = 2) +
  scale_x_log10()
summary(chocolate_df$cocoa_percent)
# Histogram of Cocoa Content
ggplot(data = chocolate_df, aes(x = cocoa_percent)) +
  geom_histogram(bins = 20, alpha = 0.80, color = "dark blue", fill = 'light blue') +
  theme_light() +
  coord_cartesian(expand = FALSE, ylim = c(0, 750)) +
  labs(x = "Cocoa Content (%)",
       y = "Count",
       title = "Distribution of Cocoa Content in Chocolates")
summary(chocolate_df$rating)
# Histogram of Chocolate Ratings by Cocoa Content
```

```r
# Create bins of various ranges of cocoa content
chocolate_df$Cocoa.Percent_bin <- cut(chocolate_df$cocoa_percent,
                                      breaks = c(40, 50, 60, 70, 80, 90,100))
# plot
ggplot(data = chocolate_df, aes(x = rating, fill = Cocoa.Percent_bin)) +
  geom_histogram(bins = 15) +
  theme_light() +
  coord_cartesian(expand = FALSE, ylim = c(0, 700)) +
  scale_fill_brewer(type = "seq",
                    palette = "YlOrBr",
                    labels = c("40-50", "50-60", "60-70", "70-80", "80-90", "90-100"),
                    name = "Cocoa Content (%)") +
  labs(x = "Rating",
       y = "Count",
       title = "Distribution of Chocolate Ratings")
library(caret)
#library(matrixStats)
set.seed(123)
#we use a training data set containing a random sample of 70% of the observation to perform with "Diabe

partition <- caret::createDataPartition(y = chocolate_df$rating, times = 1, p = 0.7, list = FALSE)

# create training data set
train_set <- chocolate_df[partition,]

# create testing data set, subtracting the rows partition to get remaining 30% of the data
test_set <- chocolate_df[-partition,]
#str(train_set)
#str(test_set)
X<-train_set[,c(7,12:17,19)]
y <- train_set$rating
x <- data.matrix(X)
x_test <- data.matrix(test_set[,c(7,12:17,19)])
y_test <- test_set$rating
RMSE <- function(true_ratings, predicted_ratings){
    sqrt(mean((true_ratings - predicted_ratings)^2))}
mu <- mean(y, na.rm = TRUE)
mu
naive_rmse <- RMSE(test_set$rating, mu)
naive_rmse
# Determine the correlation between cocoa content and chocolate rating
cor(x = train_set$cocoa_percent, y = train_set$rating, method = "pearson")

#simple plot of rating vs cocoa%
graph <- ggplot(train_set, aes(x = cocoa_percent, y = rating)) +
  geom_point() +
  geom_smooth(method = "lm", col = "light blue")+
  labs(x='Cocoa Percent', y='Rating', title='Linear Regression Plot') +
  theme(plot.title = element_text(hjust=0.5, size=20, face='bold'))+
  theme_minimal()+
  annotate("text", x = 45, y = 1.1, label = "italic(R) ^ 2 == 0.021", parse= TRUE)

graph
```

```
# Fit a linear model to predict rating based on Cocoa Content
mod1 <- lm(rating ~ cocoa_percent, data = train_set)
summary(mod1)

mod1$coef
y_hat <- mod1$coef[1] + mod1$coef[2]*test_set$cocoa_percent
sqrt(mean((y_hat - test_set$rating)^2))
#rmse = 0.4565
# Fit a linear model to predict rating based on cocoa content and other ingredients
mod2 <- lm(rating ~
                cocoa_percent+
                sweetener+
                sugar+
                cocoa_butter+
                vanilla+
                beans+
                lecithin+
                salt,
              data=train_set)
summary(mod2)
#stemMod2 <- step(mod2,direction = c("both"))
library(car)
vif_values <- vif(mod2)
vif_values

df_vif <- data.frame("Model" = c("cocoa_percent", "sweetener","sugar","cocoa_butter","vanilla","beans",
                 "VIF" = c("1.110422", "12.446042","24.155985","1.231621","1.208095","13.391249","1.2640

kbl(df_vif, booktabs = T) |>
  kable_classic(full_width = T, html_font = "Cambria")
knitr::kable(df_vif, align = "lcc")

library(corrplot)
cor1 = cor(X)
testRes = cor.mtest(X, conf.level = 0.95)
corrplot(cor1, p.mat = testRes$p, method = 'circle', type = 'lower', insig='blank',
         addCoef.col ='black', number.cex = 0.8, order = 'AOE', diag=FALSE)
library(glmnet)
mod_ridge <- glmnet(x, y, alpha = 0)
#summary(mod_ridge)
cv_model <- cv.glmnet(x, y, alpha = 0)
best_lambda <- cv_model$lambda.min
best_lambda
plot(cv_model)
best_model <- glmnet(x, y, alpha = 0, lambda = best_lambda)
coef(best_model)
y_predicted <- predict(mod_ridge, s = best_lambda, newx = x)
sst <- sum((y - mean(y))^2)
sse <- sum((y_predicted - y)^2)
rsq <- 1 - sse/sst
rsq
# 0.07255
summary(mod2)
```

```r
# R2 = 0.06869
test_set$pred_lm <- predict(best_model, x_test)
# Calculate the RMSE of the predictions
test_set |>
  summarize(rmse = RMSE(rating, pred_lm)) |>
  pull(rmse)
#rmse = 0.4378
library(randomForest)
set.seed(123)
control <- trainControl(method="cv", number = 5)
grid <- data.frame(mtry = c(1, 5, 10, 25, 50, 100))

train_rf <-  train(x, y,
                   method = "rf",
                   ntree = 150,
                   trControl = control,
                   tuneGrid = grid,
                   nSamp = 5000)

fit_rf <- randomForest(x, y, mtry = train_rf$bestTune$mtry)
plot(fit_rf)
# Create a column called pred to store the prediction from the random forest model
test_set$pred_rf <- predict(fit_rf, x_test)

# Calculate the RMSE of the predictions
test_set |>
  summarize(rmse = RMSE(rating, pred_rf)) |>
  pull(rmse)
# 0.4331
importance(fit_rf)
par(mfrow = c(1, 2))
varImpPlot(fit_rf, type = 2, main = "Variable Importance",col = 'black')
plot(fit_rf, main = "Error vs no. of trees grown")
#install.packages("kknn")
library(kknn)
grid1 = expand.grid(.k=seq(10,50, by=2))
control = trainControl(method="cv")
set.seed(123)

fit_knn = train(rating~cocoa_percent+
                sweetener+
                sugar+
                cocoa_butter+
                vanilla+
                beans+
                lecithin+
                salt, data=train_set, method="knn",
                trControl=control, tuneGrid=grid1,na.action = na.omit)
fit_knn
ggplot(fit_knn, highlight = TRUE)#k = 18
test_set$pred_knn <- predict(fit_knn, x_test)

# Calculate the RMSE of the predictions
```

```r
test_set |>
  summarize(rmse = RMSE(rating, pred_knn)) |>
  pull(rmse)
#0.4399
df <- data.frame("Model" = c("Just The Average","Simple Linear Regression", "Multivariable Regression",
                 "RMSE" = c("0.4611","0.4565", "0.4378","0.4331","0.4399"))
kbl(df, booktabs = T) |>
  kable_classic(full_width = T, html_font = "Cambria")
knitr::kable(df, align = "lcc")
```