Sentiment Analysis of Amazon Food Reviews

Project Statement

The key objective of this project is to analyze the sentiment of customers that are reviewing food products on amazon.com

This project is divided into two parts:

In Part 1 lexicon-based approach is used to gather insights on different types of sentiments experienced by customers

In Part 2 using score as target value a supervised machine learning model is built that can predict customers sentiment based on textual review.

```
conn <- dbConnect(SQLite(), "C:\\Users\\likhi\\Desktop\\MSDA\\Data Mining 2\\Dataset\\database.sqlite")

data_amazon <- dbGetQuery(conn, "SELECT * FROM Reviews")

head(data_amazon)
```

```
##   Id  ProductId         UserId                      ProfileName
## 1  1 B001E4KFG0 A3SGXH7AUHU8GW                       delmartian
## 2  2 B00813GRG4 A1D87F6ZCVE5NK                           dll pa
## 3  3 B000LQOCH0  ABXLMWJIXXAIN Natalia Corres "Natalia Corres"
## 4  4 B000UA0QIQ A395BORC6FGVXV                             Karl
## 5  5 B006K2ZZ7K A1UQRSCLF8GW1T   Michael D. Bigham "M. Wassir"
## 6  6 B006K2ZZ7K  ADT0SRK1MGOEU                   Twoapennything
##   HelpfulnessNumerator HelpfulnessDenominator Score       Time
## 1                    1                      1     5 1303862400
## 2                    0                      0     1 1346976000
## 3                    1                      1     4 1219017600
## 4                    3                      3     2 1307923200
## 5                    0                      0     5 1350777600
## 6                    0                      0     4 1342051200
##                 Summary
## 1 Good Quality Dog Food
## 2     Not as Advertised
## 3 "Delight" says it all
## 4        Cough Medicine
## 5           Great taffy
## 6           Nice Taffy
##
Text
## 1
I have bought several of the Vitality canned dog food products and have found them all to be of good quality. The product looks more like a stew than a pro
```

```
cessed meat and it smells better. My Labrador is finicky and she appreciates
this product better than  most.
## 2
Product arrived labeled as Jumbo Salted Peanuts...the peanuts were actually s
mall sized unsalted. Not sure if this was an error or if the vendor intended
to represent the product as "Jumbo".
## 3 This is a confection that has been around a few centuries.  It is a ligh
t, pillowy citrus gelatin with nuts - in this case Filberts. And it is cut in
to tiny squares and then liberally coated with powdered sugar.  And it is a t
iny mouthful of heaven.  Not too chewy, and very flavorful.  I highly recomme
nd this yummy treat.  If you are familiar with the story of C.S. Lewis' "The
Lion, The Witch, and The Wardrobe" - this is the treat that seduces Edmund in
to selling out his Brother and Sisters to the Witch.
## 4
If you are looking for the secret ingredient in Robitussin I believe I have f
ound it.  I got this in addition to the Root Beer Extract I ordered (which wa
s good) and made some cherry soda.  The flavor is very medicinal.
## 5
Great taffy at a great price.  There was a wide assortment of yummy taffy.  D
elivery was very quick.  If your a taffy lover, this is a deal.
## 6
I got a wild hair for taffy and ordered this five pound bag. The taffy was al
l very enjoyable with many flavors: watermelon, root beer, melon, peppermint,
grape, etc. My only complaint is there was a bit too much red/black licorice-
flavored pieces (just not my particular favorites). Between me, my kids, and
my husband, this lasted only two weeks! I would recommend this brand of taffy
-- it was a delightful treat.
```

We can now check the data type, dimension and other important information about the extracted data.

```
str(data_amazon)

## 'data.frame':    568454 obs. of  10 variables:
##  $ Id                    : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ ProductId             : chr  "B001E4KFG0" "B00813GRG4" "B000LQOCH0" "B0
00UA0QIQ" ...
##  $ UserId                : chr  "A3SGXH7AUHU8GW" "A1D87F6ZCVE5NK" "ABXLMWJ
IXXAIN" "A395BORC6FGVXV" ...
##  $ ProfileName           : chr  "delmartian" "dll pa" "Natalia Corres \"Na
talia Corres\"" "Karl" ...
##  $ HelpfulnessNumerator  : int  1 0 1 3 0 0 0 0 1 0 ...
##  $ HelpfulnessDenominator: int  1 0 1 3 0 0 0 0 1 0 ...
##  $ Score                 : int  5 1 4 2 5 4 5 5 5 5 ...
##  $ Time                  : int  1303862400 1346976000 1219017600 130792320
0 1350777600 1342051200 1340150400 1336003200 1322006400 1351209600 ...
##  $ Summary               : chr  "Good Quality Dog Food" "Not as Advertised
" "\"Delight\" says it all" "Cough Medicine" ...
##  $ Text                  : chr  "I have bought several of the Vitality can
ned dog food products and have found them all to be of good quality. T"| __tr
```

```
uncated__ "Product arrived labeled as Jumbo Salted Peanuts...the peanuts were
actually small sized unsalted. Not sure if t"| __truncated__ "This is a confe
ction that has been around a few centuries.  It is a light, pillowy citrus ge
latin with nuts - i"| __truncated__ "If you are looking for the secret ingred
ient in Robitussin I believe I have found it.  I got this in addition t"| __t
runcated__ ...
```

We can see that there are about 10 Columns or attributes and 568454 rows/ records in our dataset.

The amazon food review data has below attributes: * Id * Product Id - unique identifier for the product * User Id - unique identifier for the user * Profile Name * Helpfulness Numerator - number of users who found the review helpful * Helpfulness Denominator - number of users who indicated whether they found the review helpful or not * Score - rating between 1 and 5 * Time - time stamp for the review * Summary - brief summary of the review * Text - text of the review

Exploratory Data Analysis

As a first step we check if there are any empty of NUll values in the "Text" column of the dataset

```
dbGetQuery(conn, "SELECT Text
                  FROM Reviews
                  WHERE Text IS NULL")

## [1] Text
## <0 rows> (or 0-length row.names)
```

Since there are no null values in the "Text" column, each row can be treated as a document to create corpus. However, we can further explore the dataset to find any abnormalities

```
distinct_products <- dbGetQuery(conn, "SELECT DISTINCT ProductId
                  FROM Reviews ")
dim(distinct_products)

## [1] 74258     1
```

For my analysis I would like to check only popular products which can be identified as products that are receiving at least greater than 3 reviews. Thus I checked the products that have high number of reviews.

```
popular_products <- dbGetQuery(conn, "SELECT ProductId
                  FROM Reviews
                  GROUP BY ProductId
                  HAVING COUNT(Text)> 3
                  ORDER BY COUNT(Text) DESC")

dim(popular_products)

## [1] 24739     1
```

```
head(popular_products)

##    ProductId
## 1 B007JFMH8M
## 2 B002QWP8H0
## 3 B002QWP89S
## 4 B002QWHJOU
## 5 B0026RQTGE
## 6 B003B3OOPA
```

Checking the reviews on the product “B007JFMH8M”.

```
most_popluar_product <- dbGetQuery(conn, "SELECT Text
                  FROM Reviews
                  WHERE ProductId = 'B007JFMH8M'")

dim(most_popluar_product)

## [1] 913   1
```

There are about 913 reviews on this product which clearly indicates that a lot of people have used this product. We can assume that the higher review rates indicate that the product is selling more and maybe liked by customers. But we can’t say this certainty that the customers have positive sentiment towards this product as high reviews can also mean people are negatively reviewing so that others don’t buy the product.

Hence we can further explore the sentiment of customers towards all the popular products (i.e. The products having number of reviews at least greater than 3 reviews). Also I just want to analyze positive and negative sentiment reviews thus I am removing the reviews with neutral score of 3

```
data_retrieved <- dbGetQuery(conn,"SELECT *
                      FROM Reviews
                      WHERE Score != 3
                      GROUP BY ProductId
                    HAVING COUNT(Text)> 3")
dim(data_retrieved)

## [1] 23583    10

dbDisconnect(conn)

duplicate_check1 <- filter(data_retrieved, Id == 171104)
duplicate_check2 <- filter(data_retrieved, Id == 217335)
duplicate_check1$Text

## [1] "This product is a very health snack for your pup as it is made of 100
% beef liver. My puppy does all of his tricks to get this treat. It is a litt
le pricy but the container is large so it should last a long time as long as
you don't overfeed."

duplicate_check2$Text
```

```
## [1] "This product is a very health snack for your pup as it is made of 100
% beef liver. My puppy does all of his tricks to get this treat. It is a litt
le pricy but the container is large so it should last a long time as long as
you don't overfeed."
```

While exploring the data, we can see that there are two reviews made by same user as same time. This can be a case of duplicate record for products that are of same type but different size.

It would not be useful to analyze same textual review that have been given at as point of time by the same user/customer as these can be duplicate records or there is a chance that the organization applies same review to products that are same but different in size. so I have tried to remove duplicates of textual reviews from the dataset based on the UserId , Time and Text columns.

```
data <-  data_retrieved[!duplicated(data_retrieved[c("UserId","Time","Text")]
),]
dim(data)

## [1] 20292    10

head(data)

##       Id  ProductId         UserId              ProfileName
## 1 150493 0006641040  AMX0PJKV4PPNJ E. R. Bird "Ramseelbird"
## 2 171104 7310172001  AU2LNDRGFOS8J       Janice Garner "jg"
## 4  76853 B00002N8SM A392XPUTJDHSDJ                 T. Chang
## 5 374267 B00004CI84  AFV2584U13XP3              Rich "xman"
## 7 269135 B00004RAMS A2S596XESL1V2D     P. Trepanier "pTrep"
## 8 208801 B00004RAMV  A7JC62FV0BRHE       D. Wilson "Paparx"
##   HelpfulnessNumerator HelpfulnessDenominator Score       Time
## 1                   71                     72     4 1096416000
## 2                    0                      0     5 1309046400
## 4                    3                      4     1 1264896000
## 5                    0                      0     5 1349654400
## 7                   41                     41     5 1221696000
## 8                   11                     11     4 1179100800
##                                                        Summary
## 1 Read it once. Read it twice. Reading Chicken Soup With Rice
## 2                                                    very good
## 4                                    Doesn't catch fruit flies
## 5                   A Wacky Entertaining Look At The Afterlife
## 7                 This is what works.  It's all about placement
## 8                                               Best of its kind
##
Text
## 1 These days, when a person says, "chicken soup" they're probably going to
follow up those words with, "for the soul" or maybe "for the teenaged soul".
Didn't used to be that way.  Why I can remember a time when if a person said,
"chicken soup" those words were followed by an enthusiastic "with rice!".  Su
ch was the power of Maurice Sendak's catchy 1962 children's book.  I am pleas
```

ed to report that if you care to read this book again today, you will find it
hasn't dimished a jot in terms of frolicksome fun. In this book we are led t
hrough a whirlwind chicken soup year with our host, a boy who bears no little
resemblance to Sendak's other great rhyming tale "Pierre" (in looks if not de
meanor). It's a catchy flouncy bouncy combo of soup and the people who love
it so.

This is ostensibly a book meant to teach your children the
different months of the year. Each month gets its own rhythmic poem and acco
mpanying illustration. These are fairly simple pen and ink drawings with the
occasional splash of blue (in varying shades), yellow, gray, and green. You
may wonder how an author could ever hope to come up with twelve highly origin
al soup-related poems. I mean, honestly, how much is there to say about even
the fanciest soup, let alone chicken soup with rice? Quite a lot, as it happ
ens. In the cold winter months soup is supped while sliding on ice, while ce
lebrating the birthday of a snowman, and in a gusty gale as a whale. In the
spring there's robin's nest soup, soup to cure drooping roses, and soup stole
n by jealous March winds. Our hero postulates the potential joys that could
come of being a cooking pot, stewing soup or (oddly enough) as "a baubled ban
gled Christmas tree".

Not to degrade the reading skills of parents
everywhere, but I cannot recommend enough getting an audio version of this ta
le to accompany your child's reading. Though I am now a wise and cultured 26
year-old (the years have been kind to me in this, my old age) I can still rem
ember the chicken soup with rice tune. Heck, I read this entire book recentl
y and found I could do the song perfectly with each and every line. Now mayb
e you have your own particular chicken soup with rice song style that you're
just loathe to give up. If so, fine. I understand why you might not want to
taint your already existing chicken soup melody. But if you haven't found a
jingle to accompany this book, get the audio version immediately, if not soon
er. Until you can sing "Whoopy once, whoopy twice, whoopy chicken soup with
rice" with the correct oomph, you're missing out.

I take my "Chick
en Soup With Rice" readings seriously. This book was the "Chicka Chicka Boom
Boom" of its day, and still remains the catchiest method to teach kids the mo
nths of the year. It is also seriously in danger of being forgotten. So pul
l out your old accordion and strap on your dancing shoes. The time for yukki
n' it up to a merry dance of poultry broth is here. It's Sendak at his fines
t.
2
This product is a very health snack for your pup as it is made of 100% beef l
iver. My puppy does all of his tricks to get this treat. It is a little pricy
but the container is large so it should last a long time as long as you don't
overfeed.
4
I don't know how this product performs with big flies but it sucks with fruit
flies.
5
If this is what the afterlife is going to be like then I guess it won't be so
bad when it's my time though gotta stay away from anyone like Beetlejuice. T
im Burton movies are an a acquired taste while entertaining then do sometimes
seem a little out there though that's what makes these movies so entertaining
in the first place. The cast are great in this movie as they all seem to give
a 110% into their characters and while for obvious reasons some of the effect

```
s will seem dated they will still make you give a laugh as y see the hijinx o
f Beetlejuice in action.  I do advise new comers to try and watch a trailer o
r clip though as while many especially fans greatly appreciate the movie it m
ight not be for you.
## 7
I have a large yard with several moles.  I called a mole/pest removal company
.  I hired them and paid 200.00 to have about a dozen traps set (yes, they us
ed these exact traps which is why I ordered some for myself).<br /><br />Anyw
ay, they had 30 days to trap moles in my yard.  They also charged 69.00 for e
ach mole they caught.  They got 5 moles in that time.<br /><br />That may not
seem like many, but if you read about moles, you'll find out they are not lik
e mice or rats.  They breed slowly and live alone.  They reproduce once per y
ear and maybe have 2-4 offspring of which maybe half will live in natural con
ditions.  When you see an area or network of mole tunnels (your grass pushed
up), that's just one mole... If you study the tunnels, you'll usually see it
comes in from the edge of your yard where there may be more moisture (forest
or wild area).<br /><br />You just need to look at the branching of the tunne
ls and find a few areas where you can guess the mole may be re-using that sec
tion to go back and forth.<br /><br />Once you locate a good spot, gently pus
h the grass down to collapse the tunnel, and set the trap.  Be sure to set th
e trap so the spikes that go in the ground (not the spikes that kill the mole
) are not right in the middle of the mole tunnel.  The idea (obviously) is to
set the trap in an area the mole will try to use again.  When the mole tries
to fix the tunnel, bam!<br /><br />I just trapped my first mole today.  I saw
the spring of the trap was down, took the trap up, and the mole was dead unde
rneath.<br /><br />This trap does work to kill the mole.  YOu just need to pu
t it in the right place and set it correctly.<br /><br />The guy who worked f
or the pest control company told me most of this and it really makes a differ
ence.<br /><br />I'm here to buy a few more traps.  I would suggest getting t
wo traps for each distinct area you think there may be a mole.  I plan to jus
t keep rotating 4-6 traps until all the moles are gone.
## 8
Large, therefore keeps its content for a while and easy to fill/use/reuse.  M
y wife is allergic so Ive been at this for years.<br />You'll get a year out
of each at least but the thin plastic bottles do crack from sun exposure over
time.<br />They should be nice thick plastic bottle but then you would have t
o pay more and NOT replace them every 2 years.  Why we live on landfills  :-c
<br />These are the Best bee traps Ive tried and I will keep buying them.<br
/><br />PS The real trick is finding which brew inside the jar keeps your loc
al bees coming back for more.  A mixture of beer, water and pinch of soap (to
film the top layer with something slippery and prevent the beer from evaporat
ing) is most effective ive found.
```

Converting the UNIX time to real date format

```
data$Time <- lubridate::as_datetime(data$Time)
data$Year <- lubridate::year(data$Time)

unique(data$Year)

##  [1] 2004 2011 2010 2012 2008 2007 2009 2002 2005 2006 2003
```

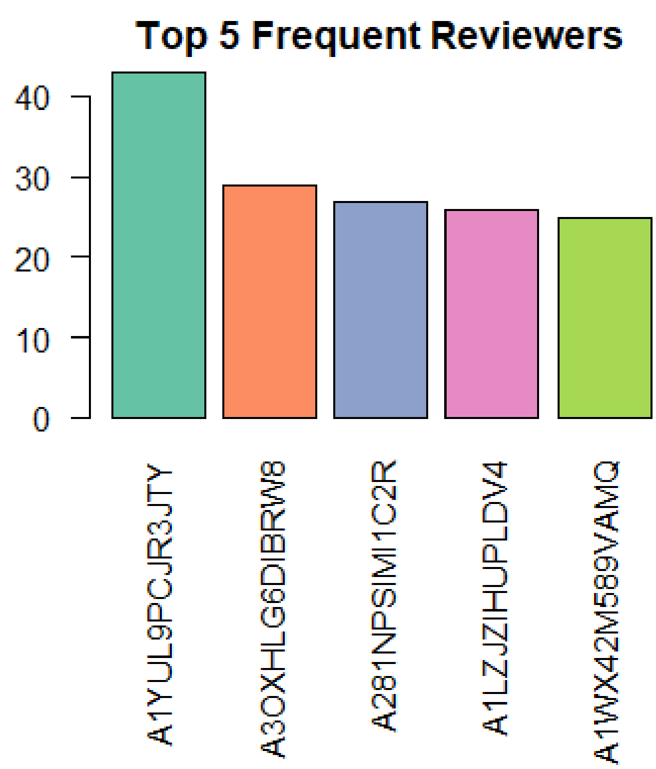
As, I have already removed the neutral rating score of 3 from my dataset it would be good add a new attribute into the data which gives out true (1) for Score<3 or false (0) for Score>3 as at the end of my analysis I would validate the positive and negative sentiment generated from text reviews.

```
data$Negative_Review <- as.factor(data$Score < 3)

head(data[1:4,12])

## [1] FALSE FALSE TRUE  FALSE
## Levels: FALSE TRUE
```

Data Visualization

First, we would like to examine the customers who have reviewed most of the food products from the selected data of popular products. Any customer who has given 25 or above reviews on food products over the years is considered a frequent reviewer.

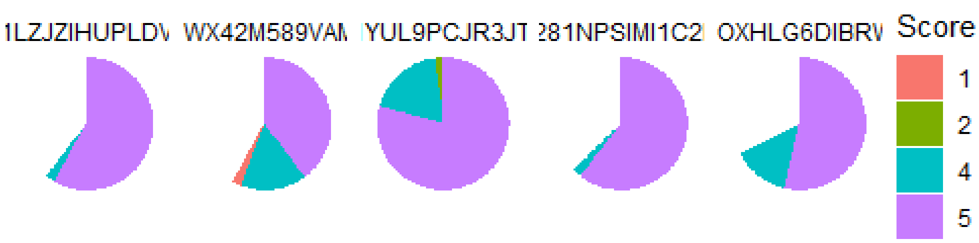
```
user_count <-  data %>%
                    count(UserId)
par(mar=c(9, 9, 2, 1))
user_count <- user_count[order(-user_count$n),]
x <- user_count[1:5,]
cols <- brewer.pal(5, "Set2")
barplot(height=x$n, names=x$UserId, col=cols, las = 2, main="Top 5 Frequent R
eviewers")
```



```
x$UserId

## [1] "A1YUL9PCJR3JTY" "A3OXHLG6DIBRW8" "A281NPSIMI1C2R" "A1LZJZIHUPLDV4"
## [5] "A1WX42M589VAMQ"
```

As these are the customers who have given most of the reviews, it would be interesting to see the distribution of Score (rating) that they have provided to different products

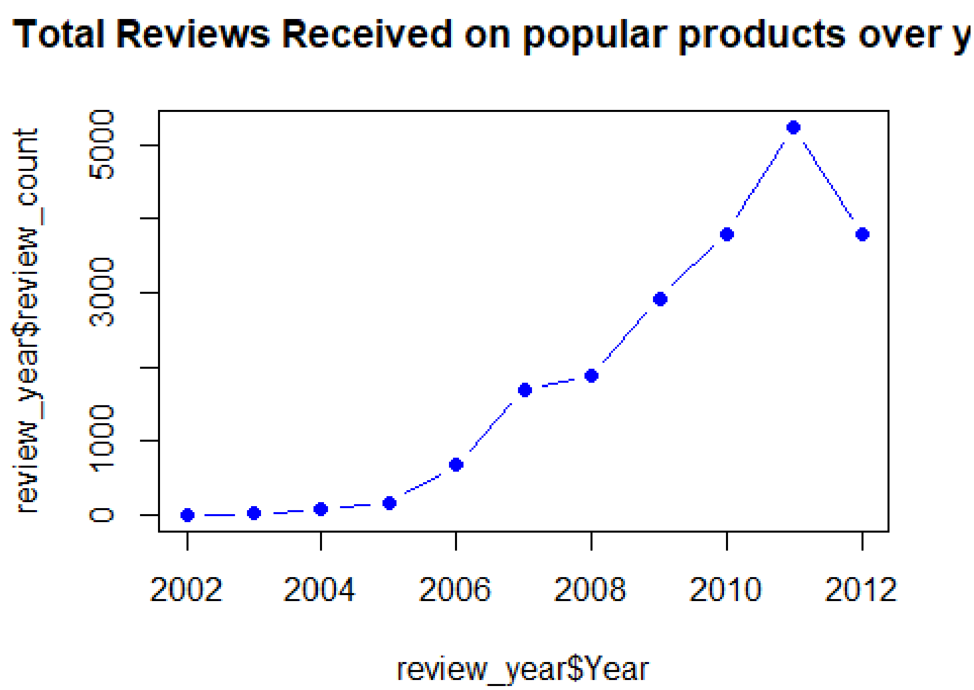
```
top_user_review <- data[data$UserId %in% c("A1YUL9PCJR3JTY","A3OXHLG6DIBRW8",
"A281NPSIMI1C2R","A1LZJZIHUPLDV4","A1WX42M589VAMQ"),]

top_user_score <-  top_user_review %>%
                     group_by(UserId) %>%
                       count(Score)

top_user_score$UserId <- factor(top_user_score$UserId)
top_user_score$Score <- factor(top_user_score$Score)

ggplot(data=top_user_score, aes(x=" ", y=n, group=Score, colour=Score, fill=S
core)) +
         geom_bar(width = 1, stat = "identity") +
         coord_polar("y", start=0) +
         facet_grid(.~ UserId) +theme_void()
```



Seeing the above plot we can say that frequent reviewers are usually providing good score rating (5 & 4) and there are hardly any negative ratings provided by these customers. Using this information company can encourage these frequent reviewers to reviewer more items which would ultimately enhance the brand value.

Since we have data from 2002 to 2012, which is about 10 years of data. It would be interesting to see how many products are getting more than 3 reviews per each year.

```
review_year <- data %>%
  select(Text, Year) %>%
  group_by(Year) %>%
  summarise(review_count = n())
plot(review_year$Year, review_year$review_count,type = "b", pch = 19, col = "
blue",
     main="Total Reviews Received on popular products over year")
```

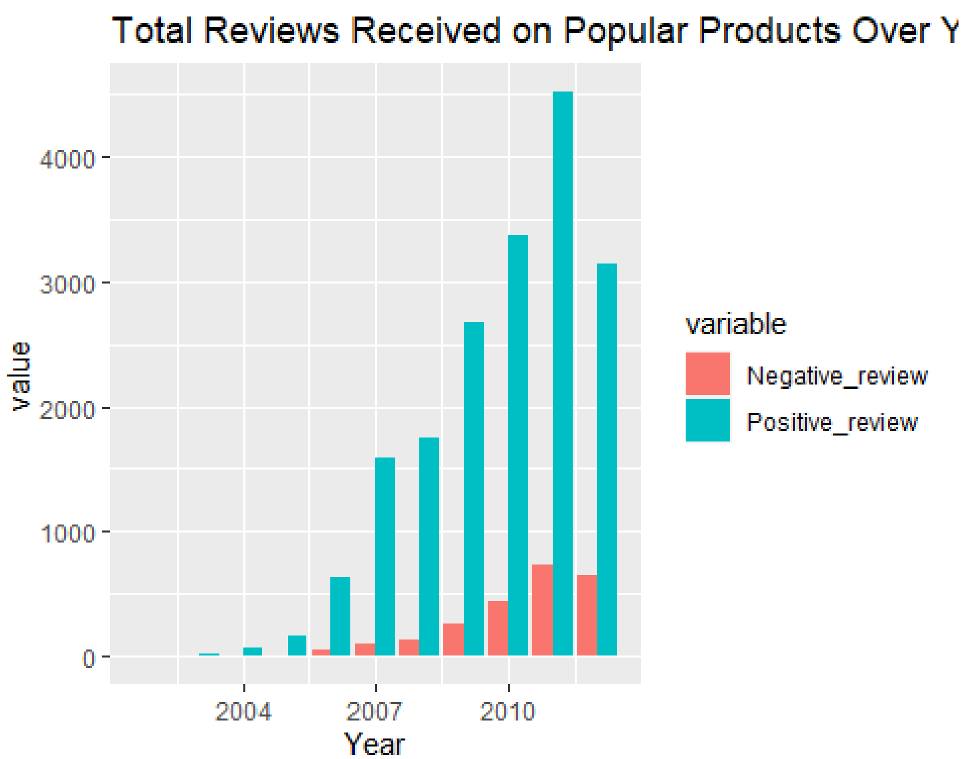


We can see that there has been an incremental growth in the number products receiving greater than 3 reviews each year however there is a slight decrease from 2011 to 2012 which is indicating that there might be increase in number of reviews but a slight decrease in popular product reviews.

It would be good to see if this increase is only in the positive reviews or if its in both negative as well as positive reviews.

```
review_neg <- data %>%
      group_by(Year) %>%
      count(Negative_Review)
pos_check1 <- as.data.frame(filter(review_neg, Negative_Review == "FALSE"))
neg_check2 <- as.data.frame(filter(review_neg, Negative_Review == "TRUE"))
```

```
neg_check2 <- neg_check2 %>% add_row(Year = 2002, n = 0)
neg_check2 <- neg_check2[order(neg_check2$Year),]
review_year <- as.data.frame(review_year)
review_year$Negative_review <- neg_check2$n
review_year$Positive_review <- pos_check1$n
reshape_data <- reshape2::melt(review_year,id.vars="Year")
barchart_data <- reshape_data[12:33,]

ggplot(barchart_data) +  geom_bar(aes(x=Year,y=value,fill=variable), stat="id
entity",position="dodge")+
  ggtitle("Total Reviews Received on Popular Products Over Years")
```



We can see that over the years there has been increase in positive as well as negative corresponding to the total number of reviews on popular products.

Data Preprocessing

Since I want to use the text data to check the sentiment of customers reviews, as a first step corpus is created for text data

Convert all letters to lowercase

```
data$Text <- stringr::str_to_lower(data$Text)
```

Remove special character strings such as websites and email

```
data$Text <- qdapRegex::rm_url(
  data$Text,
  replacement = " ",
  clean = TRUE
)

data$Text <- qdapRegex::rm_hash(
  data$Text,
  replacement = " ",
  clean = TRUE
)
data$Text <- qdapRegex::rm_tag(
  data$Text,
  replacement = " ",
  clean = TRUE
)
data$Text <- qdapRegex::rm_emoticon(
  data$Text,
  replacement = " ",
  clean = TRUE
)
data$Text <- qdapRegex::rm_email(
  data$Text,
  replacement = " ",
  clean = TRUE
)
```

Remove stop words

```
data$Text <- tm::removeWords(
  x = data$Text,
  words = tm::stopwords(kind = "SMART")
)
data$Text <- tm::removeWords(
  x = data$Text,
  words = tm::stopwords(kind = "english")
)
data$Text <- tm::removeWords(
  x = data$Text,
  words = qdapDictionaries::Top200Words
)
```

Get rid of extra white space.

```
data$Text <- trimws(stringr::str_replace_all(
  string = data$Text,
  pattern = "\\s+",
  replacement = " "
))
```

Removing Punctuation and Numbers

```r
data$Text <- tm::removePunctuation(
  x = data$Text
)

data$Text <- tm::removeNumbers(
  x = data$Text
)
```

Create Corpus

```r
Corpus_reviews <- iconv(data$Text)
Corpus_reviews <- tm::VCorpus(tm::VectorSource(data$Text))
tm::inspect(Corpus_reviews[[15]])
```

```
## <<PlainTextDocument>>
## Metadata:  7
## Content:  chars: 265
##
## purchased product recently teenaged son recurring asthmaimagine delight re
lief finally finding herbal works works rapidly tea quick easy prepare reliev
es chest constriction opens airways clears son wheezing  traditional medicina
ls keeping doctor office steroid free
```

Removing White space from corpus

```r
Corpus_reviews <- tm::tm_map(Corpus_reviews, tm::stripWhitespace)
```

Creating Document Term Matrix of the review corpus

```r
DocumentTermMatrix_reviews <- tm::DocumentTermMatrix(Corpus_reviews)
```

Remove sparse terms.

```r
DocumentTermMatrix_reviews <- tm::removeSparseTerms(
  DocumentTermMatrix_reviews,
  0.995
)
```

Create a integer matrix equivalent to the term document matrix

```r
M <- as.matrix(DocumentTermMatrix_reviews)
M[1:5,1:5]
```

```
##     Terms
## Docs absolutely acid actual add added
##    1          0    0      0   0     0
##    2          0    0      0   0     0
##    3          0    0      0   0     0
##    4          0    0      0   0     0
##    5          0    0      0   0     0
```

```r
dim(M)
```

```
## [1] 20292  1183
```

```r
term_frequency <- data.frame(
  Term = colnames(M),
  Frequency = colSums(M),
  stringsAsFactors = FALSE
)
term_frequency <- term_frequency[order(term_frequency$Frequency),]

term_frequency
```

```
##                        Term Frequency
## advertised       advertised       105
## delightful       delightful       105
## brings               brings       106
## grab                   grab       106
## saved                 saved       106
## comparable       comparable       107
## current             current       107
## reasons             reasons       107
## writing             writing       107
## includes           includes       108
## previously       previously       108
## beware               beware       109
## quantities       quantities       109
## returned           returned       109
## comment             comment       110
## favor                 favor       110
## worst                 worst       110
## discount           discount       111
## incredible       incredible       111
## offering           offering       111
## discontinued   discontinued       112
## lighter             lighter       112
## multiple           multiple       112
## present             present       112
## carefully         carefully       114
## dollar               dollar       114
## exact                 exact       114
## nasty                 nasty       114
## offers               offers       114
## robust               robust       114
## watching           watching       114
## worried             worried       114
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## seeds                    seeds        565
## wanted                  wanted        565
## nuts                      nuts        566
## ingredient          ingredient        571
## lemon                    lemon        571
## container            container        572
## fish                      fish        572
## bowl                      bowl        573
## disappointed   disappointed        578
## week                      week        578
## ginger                  ginger        580
## weight                  weight        581
## gave                      gave        584
## online                  online        584
## cold                      cold        587
## spicy                    spicy        587
## quickly                quickly        591
## brown                    brown        594
## popcorn                popcorn        594
## ice                        ice        595
## husband                husband        599
## works                    works        603
## cinnamon              cinnamon        606
## version                version        607
## cake                      cake        608
## difference          difference        608
## amazing                amazing        609
## side                      side        610
## bitter                  bitter        617
## prefer                  prefer        617
## life                      life        618
## gift                      gift        620
## smooth                  smooth        623
## cook                      cook        625
## pieces                  pieces        626
## canned                  canned        628
## open                      open        629
## cans                      cans        638
```

```
## heat                          heat         640
## stars                        stars         640
## gum                            gum         641
## cheaper                    cheaper         642
## money                        money         648
## soy                            soy         655
## chips                        chips         656
## fiber                        fiber         656
## cost                          cost         658
## reviews                    reviews         661
## longer                      longer         662
## cooking                    cooking         666
## flavored                  flavored         667
## sodium                      sodium         673
## flour                        flour         675
## fine                          fine         678
## smell                        smell         680
## deal                          deal         682
## dried                        dried         687
## packaging                packaging         687
## save                          save         689
## recommended            recommended         692
## ounce                        ounce         695
## recipe                      recipe         695
## started                    started         695
## juice                        juice         696
## absolutely              absolutely         702
## arrived                    arrived         707
## peanut                      peanut         707
## morning                    morning         709
## drinking                  drinking         714
## rich                          rich         716
## serving                    serving         717
## decided                    decided         720
## gluten                      gluten         723
## breakfast                breakfast         725
## couple                      couple         732
## meat                          meat         735
## kids                          kids         738
## coconut                    coconut         755
## times                        times         761
## cups                          cups         764
## loved                        loved         764
## received                  received         769
## bar                            bar         772
## fact                          fact         776
## ago                            ago         777
## wheat                        wheat         781
## href                          href         783
## problem                    problem         783
```

```
## item                       item        789
## syrup                     syrup        804
## days                       days        811
## bread                     bread        813
## variety                 variety        820
## meal                       meal        822
## boxes                     boxes        832
## red                         red        841
## vanilla                 vanilla        843
## light                     light        859
## months                   months        864
## powder                   powder        864
## honey                     honey        867
## minutes                 minutes        871
## pasta                     pasta        881
## white                     white        881
## teas                       teas        889
## health                   health        894
## top                         top        898
## cream                     cream        899
## cereal                   cereal        900
## corn                       corn        903
## tasting                 tasting        911
## blend                     blend        913
## tasted                   tasted        918
## things                   things        928
## case                       case        932
## cookies                 cookies        932
## bars                       bars        934
## bottle                   bottle        946
## dark                       dark        950
## family                   family        951
## purchase               purchase        955
## treat                     treat        960
## dry                         dry        962
## review                   review        971
## making                   making        976
## feel                       feel        982
## cats                       cats        983
## full                       full        984
## black                     black        985
## strong                   strong        994
## half                       half        995
## diet                       diet        997
## purchased             purchased        999
## low                         low       1015
## amount                   amount       1017
## treats                   treats       1023
## protein                 protein       1028
## beans                     beans       1030
```

```
## cheese                    cheese       1043
## brands                    brands       1048
## loves                      loves       1057
## soup                        soup       1063
## thought                  thought       1067
## bad                          bad       1068
## company                  company       1069
## fruit                      fruit       1079
## tasty                      tasty       1090
## worth                      worth       1107
## added                      added       1112
## happy                      happy       1114
## snack                      snack       1121
## pretty                    pretty       1140
## excellent              excellent       1154
## size                        size       1158
## dogs                        dogs       1166
## calories                calories       1183
## package                  package       1184
## stores                    stores       1192
## butter                    butter       1200
## ensive                    ensive       1200
## shipping                shipping       1202
## real                        real       1227
## wonderful              wonderful       1251
## highly                    highly       1260
## ure                          ure       1273
## fat                          fat       1292
## grocery                  grocery       1303
## regular                  regular       1306
## bags                        bags       1315
## enjoy                      enjoy       1321
## buying                    buying       1331
## candy                      candy       1338
## foods                      foods       1342
## cat                          cat       1361
## easy                        easy       1366
## ordered                  ordered       1371
## eating                    eating       1414
## hard                        hard       1425
## perfect                  perfect       1439
## high                        high       1444
## healthy                  healthy       1445
## chicken                  chicken       1454
## pack                        pack       1488
## rice                        rice       1527
## local                      local       1544
## natural                  natural       1576
## green                      green       1618
## lot                          lot       1632
```

```
## salt                         salt       1637
## products                 products       1638
## quality                   quality       1672
## stuff                       stuff       1708
## brand                       brand       1720
## flavors                   flavors       1742
## ingredients           ingredients       1744
## fresh                       fresh       1749
## bit                           bit       1771
## nice                         nice       1780
## recommend               recommend       1809
## favorite                 favorite       1814
## makes                       makes       1826
## free                         free       1854
## tastes                     tastes       1870
## sauce                       sauce       1873
## order                       order       1911
## milk                         milk       1916
## drink                       drink       1955
## hot                           hot       1966
## organic                   organic       2067
## delicious               delicious       2074
## bought                     bought       2077
## mix                           mix       2077
## dog                           dog       2175
## years                       years       2179
## store                       store       2246
## cup                           cup       2273
## add                           add       2283
## sweet                       sweet       2329
## box                           box       2442
## bag                           bag       2502
## eat                           eat       2821
## chocolate               chocolate       2961
## sugar                       sugar       3038
## price                       price       3197
## buy                           buy       3333
## amazon                     amazon       4475
## love                         love       4816
## coffee                     coffee       5031
## food                         food       5070
## product                   product       6276
## flavor                     flavor       6489
## taste                       taste       6810
## tea                           tea       7121
```

```
wordcloud::wordcloud(
  words = term_frequency$Term,
  freq = term_frequency$Frequency,
  max.words = 25,
```

```
  random.order = FALSE,
  colors = viridis::viridis(100)
)
```

From the word cloud, we can see that there are few words like “amazon” or “product” which are not very informative as this data set is all about amazon food reviews.

Removing some uninformative words

```
Corpus_reviews <- tm::tm_map(Corpus_reviews,tm::removeWords, c("amazon", "ord
er","buy","food","product","bought","add","knowing","common"))
```

Now, visualizing the word cloud

```
DocumentTermMatrix_reviews <- tm::DocumentTermMatrix(Corpus_reviews)
DocumentTermMatrix_reviews <- tm::removeSparseTerms(
  DocumentTermMatrix_reviews,
  0.995
)
M <- as.matrix(DocumentTermMatrix_reviews)
term_frequency <- data.frame(
  Term = colnames(M),
  Frequency = colSums(M),
  stringsAsFactors = FALSE
)
term_frequency <- term_frequency[order(term_frequency$Frequency),]
```

```
wordcloud::wordcloud(
  words = term_frequency$Term,
  freq = term_frequency$Frequency,
  max.words = 25,
  random.order = FALSE,
  colors = viridis::viridis(100)
)
```

Looking at the word cloud we can make the below deductions:

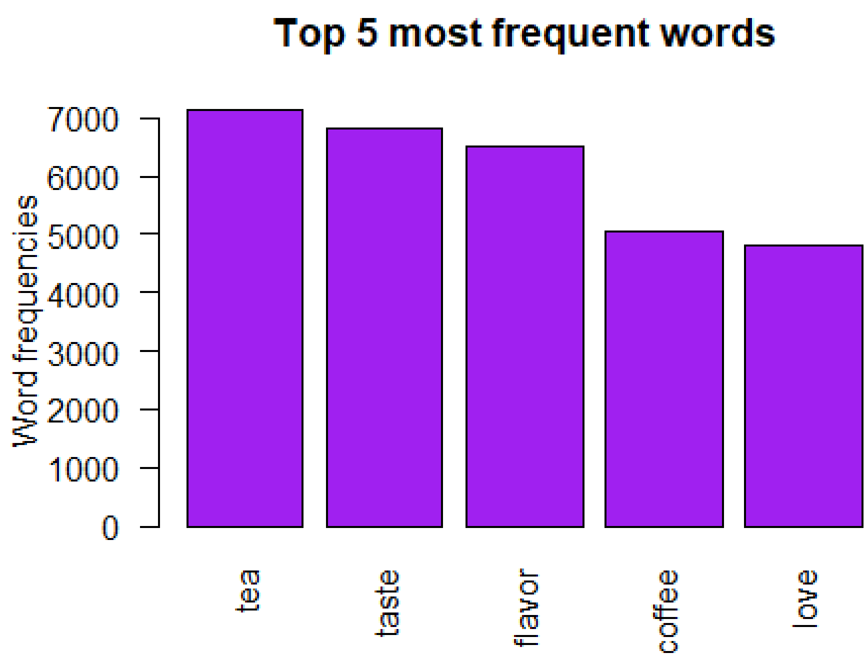
- looks like tea is a popular product which is greatly reviewed by people. “Coffee” is also appearing in that word cloud which intuitively tells us that people are reviewing beverages more compared to other food products.
- Also there are few key words like “delicious” & “love” indicates that overall people reviewing these products have a more of positive sentiment.
- The use of words like “price”, “taste” and “flavor” intuitively tells that the value of a product and products taste as well as flavor influences customer’s sentiment. It looks like “taste” and “flavor” has greater influence on the customers review than the “price” of product.

```
dim(term_frequency)

## [1] 1174    2

barplot(term_frequency[1174:1170,]$Frequency, las = 2, names.arg = term_frequ
ency[1174:1170,]$Term,
```

```
        col ="purple", main ="Top 5 most frequent words",
        ylab = "Word frequencies")
```



Seeing the above barplot we can say that beverages like tea and coffee are most reviewed products as the frequency of these terms is high. Also words like "love" appear more in the reviews indicating that most of the reviews would be positive.

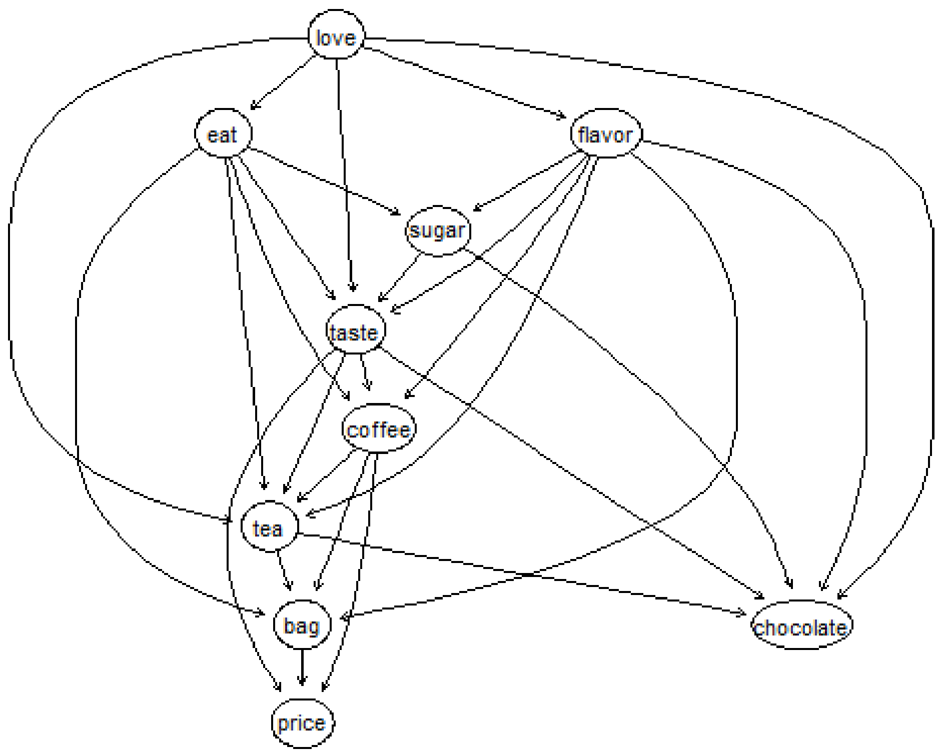
Building a bayesian network for Top 10 frequent words

```
term_frequency[1174:1165,]$Term

##  [1] "tea"       "taste"     "flavor"    "coffee"    "love"      "price"
##  [7] "sugar"     "chocolate" "eat"       "bag"

Network <- as.data.frame(M)
Bn <- Network[,c("tea", "taste", "flavor", "coffee","love" ,"price","sugar",
"chocolate" ,"eat", "bag"  )]

model_amazon <- bnlearn::hc(Bn)
bnlearn::graphviz.plot(model_amazon,
                       shape = "ellipse")
```



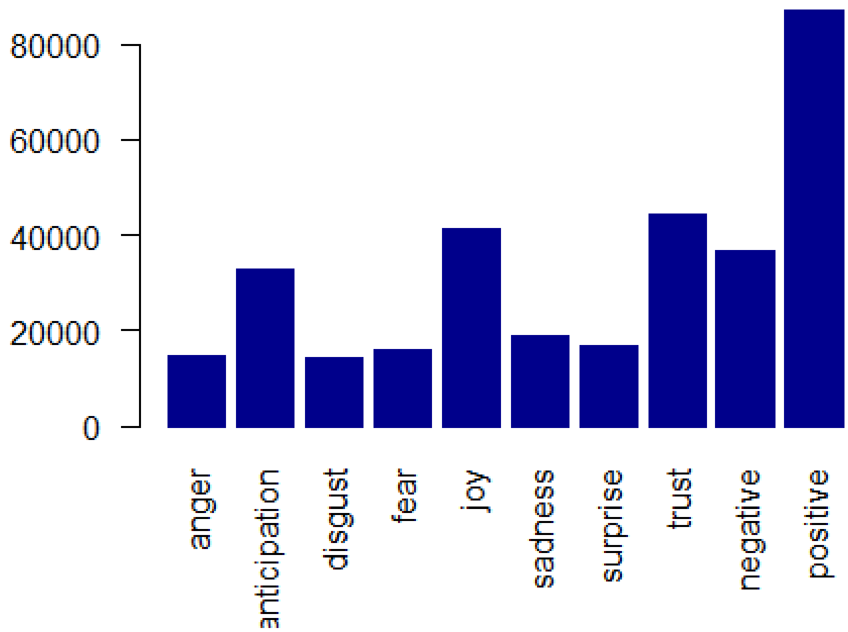
This bayesian network is complex but one key deduction we can make from the network is that the conditional probability of the word “tea” appearing in the documents is dependent on the words “love”, “taste” and “flavor” appearing in the document. This means that the product tea is associated with a positive sentiment word of love.

Using syuzhet Lexicon for sentiment analysis

```
sentiment <- syuzhet::get_nrc_sentiment(data$Text)
head(sentiment)

##   anger anticipation disgust fear joy sadness surprise trust negative posi
tive
## 1     4            8       5    6  13       7        6    11       15
24
## 2     1            2       1    1   1       1        1     2        1
2
## 3     0            0       0    0   0       0        0     0        0
0
## 4     1            2       1    2   2       1        2     2        1
5
## 5     1            2       2    3   0       2        2     2        6
0
## 6     1            4       0    2   4       0        2     6        3
7

sentiment_M <- as.matrix(sentiment)
barplot(sentiment_M, border = "dark blue",las = 2)
```



From the above plot showing frequency of each sentiment we can say that most of the reviews are positive followed by trust and joy. There are less negative sentiment in customer reviews when compared to the positive reviews. Also the prevalence of anger, disgust, fear, sadness and surprise sentiments which is a good sign for overall foods that are sold on amazon website.

Building a model for sentiment prediction

Since we have already built the sparse document term matrix we can now split the text data into training set and testing set which would be used to train our model for sentiment prediction.

```
review_df <- as.data.frame(M)
colnames(review_df) <- make.names(colnames(review_df))
review_df$Negative_reviews <- data$Negative_Review

set.seed(813)
split <- caTools::sample.split(review_df$Negative_reviews, SplitRatio=0.7)
train_reviews <- subset(review_df, split == TRUE)
test_reviews <- subset(review_df, split == FALSE)
```

Considering a baseline model that predicts all predictions as positive,

```
table(test_reviews$Negative_reviews)
```

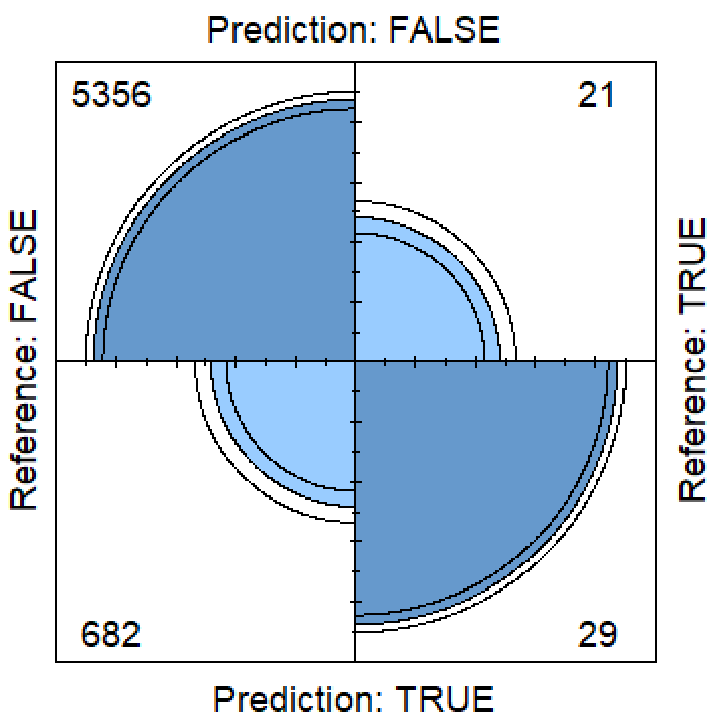
```
##
## FALSE  TRUE
##  5377   711
```

Then the accuracy of out baseline model is 5377/(5377+711) = 0.883.

First, I am building a Recursive Partitioning and Regression Trees (rpart) model to predict the positive and negative sentiments

```
review_model <- rpart::rpart(Negative_reviews ~ ., data = train_reviews, meth
od ="class")
predict_m <- predict(review_model, newdata = test_reviews, type="class")

cm <- caret::confusionMatrix(test_reviews$Negative_reviews,predict_m)
fourfoldplot(cm$table)
```




```
cm

## Confusion Matrix and Statistics
##
##           Reference
## Prediction FALSE TRUE
##      FALSE  5356   21
##      TRUE    682   29
##
##                Accuracy : 0.885
##                  95% CI : (0.876, 0.892)
##     No Information Rate : 0.992
```

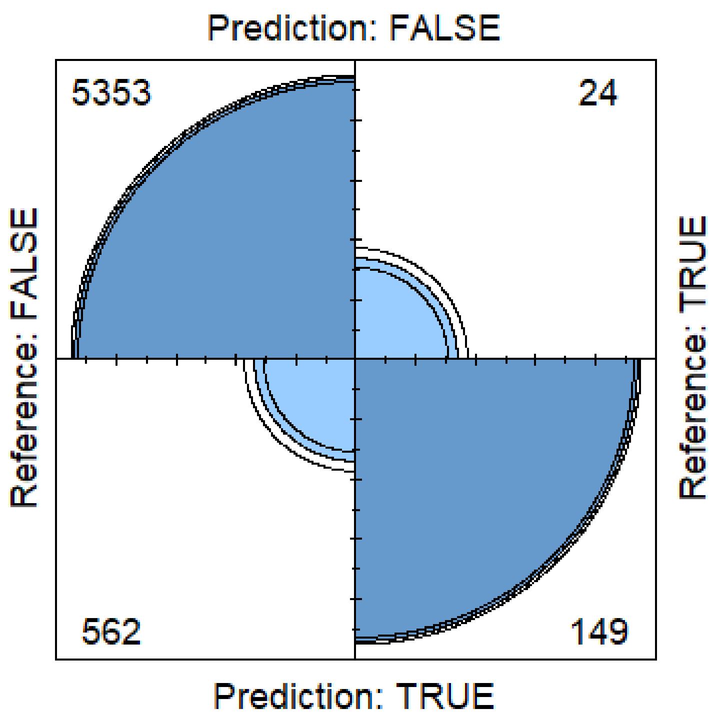
```
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.062
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.8870
##             Specificity : 0.5800
##          Pos Pred Value : 0.9961
##          Neg Pred Value : 0.0408
##              Prevalence : 0.9918
##          Detection Rate : 0.8798
##    Detection Prevalence : 0.8832
##       Balanced Accuracy : 0.7335
##
##        'Positive' Class : FALSE
##
```

The accuracy of the ecursive Partitioning and Regression Trees (rpart) model is about 0.885 which is indicating that is model has a slignt improvement on accurately predicting positive and negative sentiments compared to baseline.

Next, I am building a Support Vector Machine model to make sentiment predictions

```
svm_model <- e1071::svm(Negative_reviews ~ ., data = train_reviews)
predict_svm <- predict(svm_model, test_reviews)

cm2 <- caret::confusionMatrix(test_reviews$Negative_reviews,predict_svm)
fourfoldplot(cm2$table)
```




```
cm2

## Confusion Matrix and Statistics
##
##           Reference
## Prediction FALSE TRUE
##      FALSE  5353   24
##      TRUE    562  149
##
##                Accuracy : 0.904
##                  95% CI : (0.896, 0.911)
##     No Information Rate : 0.972
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.305
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.905
##             Specificity : 0.861
##          Pos Pred Value : 0.996
##          Neg Pred Value : 0.210
##              Prevalence : 0.972
##          Detection Rate : 0.879
##    Detection Prevalence : 0.883
##       Balanced Accuracy : 0.883
##
```

```
##        'Positive' Class : FALSE
##
```

The accuracy of the Support Vector Machine model is about 0.904 which is better than the initial Recursive Partitioning and Regression Trees model that was used

Thus, it would be good to use Support Vector Machine model for predicting positive & negative sentiment of customers based on their text reviews.

Conclusion

Through the analysis done in this project we are able to analyze the sentiments of customers and gain some insights based on their reviews that can help the organization in future strategy and roadmap development. Also we are able to predict the positive and negative sentiment of customer based on their textual reviews using a model that has accuracy of about 0.9.

References

1. https://www.kaggle.com/snap/amazon-fine-food-reviews
2. J. McAuley and J. Leskovec. From amateurs to connoisseurs: modeling the evolution of user expertise through online reviews. WWW, 2013.