Project4-demo

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Prepare data

review/helpfulness: fraction of users who found the review helpful review/score: rating of the product review/time: time of the review (unix time)

```
library(dplyr)
```

```
##
## 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(tidyr)
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 3.2.4
```

```
load('/Users/sunxiaohan/Desktop/project4/data_new.Rdata')
load('/Users/sunxiaohan/Desktop/project4/user.table.Rdata')
load('/Users/sunxiaohan/Desktop/project4/product.table.Rdata')
dim(data_new)
```

```
## [1] 505190     20
```

```
dim(user.table)
```

```
## [1] 3490    5
```

```
dim(product.table)
```

```
## [1] 4250    4
```

```r
#calculate the sd
data_new[,'dif']=(data_new$review_score-data_new$PReview_ave)^2

# summarise sd for each individual user
user.sd=data_new%>%
                group_by(review_userid)%>%
                summarize(
                  sd_total=mean(dif,na.rm=T)
                )

user.table=left_join(user.table,user.sd,by='review_userid')
user.table=na.omit(user.table)
user.table=user.table[order(user.table$sd_total),]


word_for_user=data_new%>%
  group_by(review_userid)%>%
  summarize(
    word_ave=mean(word_count)
  )
```

Find Connoisseurs

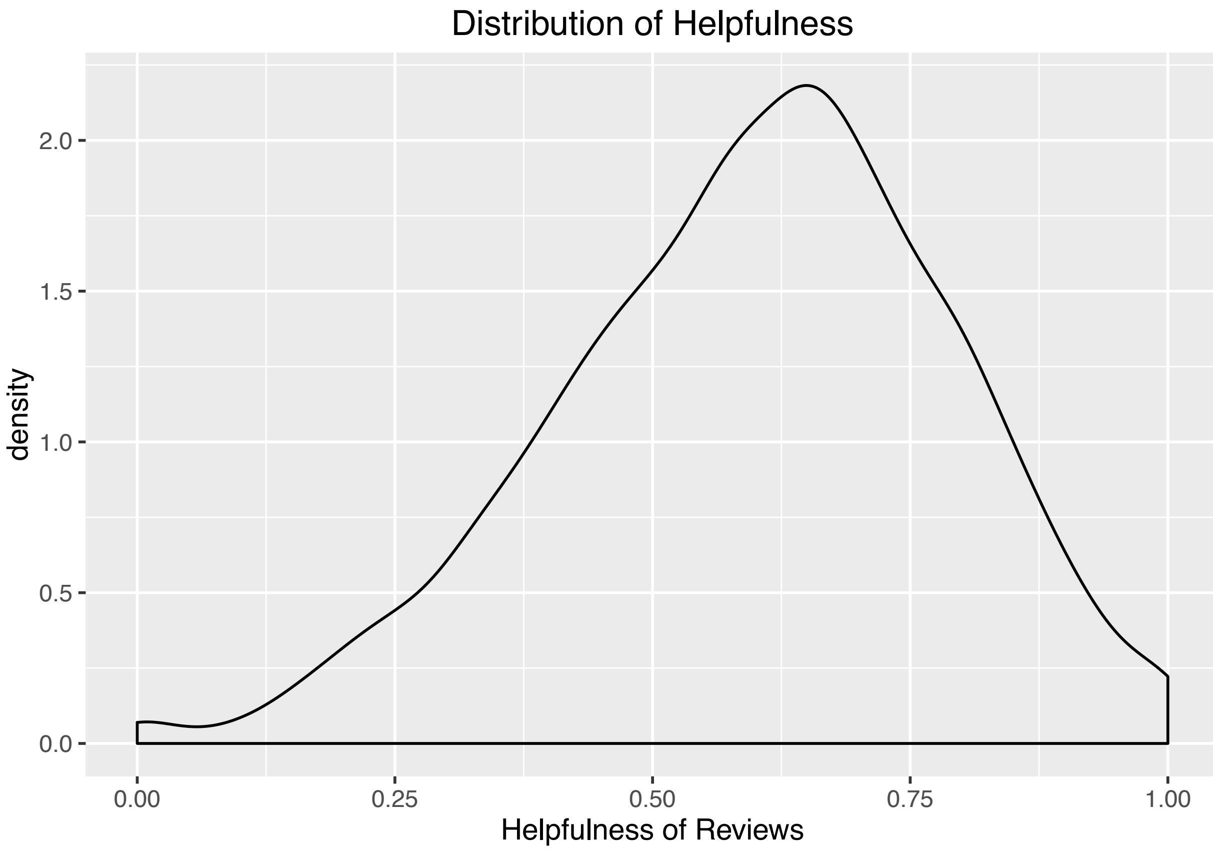
Critiria

```
* reviews have over 5 votes
* reviews have over 0.6 helpfulness ratio
* user need to write at least 5 reviews
* product should have at least 100 reviews
* calculate the variance of it to the overall variance and choose the top 500
```

```r
# user should write at least 5 reviews
user.filter=filter(user.table,user.count>5)
dim(user.filter)
```

```
## [1] 3484    6
```

```r
#distribution of helpfulness
ggplot()+geom_density(aes(user.table$UReview_help))+xlab('Helpfulness of Reviews')+ggtitle('Distributio
```




```
quantile(user.table$UReview_help,0.60)
```

```
##       60%
## 0.6595542
```

```
# Select 60% quantile as the cutting point
user.filter=filter(user.filter,UReview_help>0.6)
dim(user.filter)
```

```
## [1] 1834    6
```

```
# At least 5 user read this review
user.filter=filter(user.filter,UReview_read>5)
dim(user.filter)
```

```
## [1] 757   6
```

```
# Choose the top 500 as Connoisseurs
connoi=user.filter[1:500,]
#connoi=left_join(connoi,user.table,by='review_userid')
#save(connoi,file='connoi.Rdata')
```

Find Extreme Case

Criteria

```
* User should write at least 5 reviews
* The helpfulness of reviews should be smaller than 0.4
```

```
extreme.raw=user.table[order(user.table$sd_total,decreasing = T),]
dim(extreme.raw)
```

```
## [1] 3484    6
```

```
# user should write at least 10 reviews
extreme=filter(extreme.raw,user.count>5)
dim(extreme)
```

```
## [1] 3484    6
```

```
# the helpfulness of reviews should be at most 0.4
#quantile(user.table$UReview_help,0.40)
extreme=filter(extreme,UReview_help<0.4)
dim(extreme)
```

```
## [1] 538   6
```

```
# choose the top 500 as extreme case
extreme=extreme[1:500,]
head(extreme)
```

```
## Source: local data frame [6 x 6]
##
##    review_userid user.count UReview_ave UReview_read UReview_help
##            (chr)      (int)       (dbl)        (dbl)        (dbl)
## 1 A2YM6JTQIBZ8YC         54    1.222222     42.09259    0.1971570
## 2  ASU5IH3CM6XXE        115    1.486957     39.83478    0.2308785
## 3 A171WA0E3DIXXM         61    1.000000     29.59016    0.3539053
## 4 A3R32VYVC8IJB9         60    1.600000     22.13333    0.2579220
## 5 A24PA46807ED7J         55    1.145455     16.36364    0.2192424
## 6 A1ECVYFEXREVC7         59    1.254237     14.94915    0.1923540
## Variables not shown: sd_total (dbl)
```

```
#save(extreme,file='extreme.Rdata')
```

Find the Amateurs

Critetia

Amateurs=General - Connoisseurs

```
find1=left_join(user.table,connoi,by='review_userid')
find1[,'index']=seq(1:nrow(find1))
find2=filter(find1,user.count.y!='NA')
ame=user.table[-find2$index,]
head(ame)
```

```
## Source: local data frame [6 x 6]
##
##    review_userid user.count UReview_ave UReview_read UReview_help
##            (chr)      (int)       (dbl)        (dbl)        (dbl)
## 1 A204D78BPJEF2W         64    5.000000   0.78125000    0.9166667
## 2 A2SRPX9AZVAMWT         70    5.000000   0.05714286    0.5000000
## 3 A2YIHBD7MPNTC9        112    5.000000   0.16071429    0.4166667
## 4 A3FVISMTESSRUL        234    5.000000   0.11111111    1.0000000
## 5  AX52ULYSK82AF         57    4.192982   1.08771930    0.7187500
## 6 A2IKWMHSHKRLGG         54    4.851852   1.25925926    0.6333333
## Variables not shown: sd_total (dbl)
```

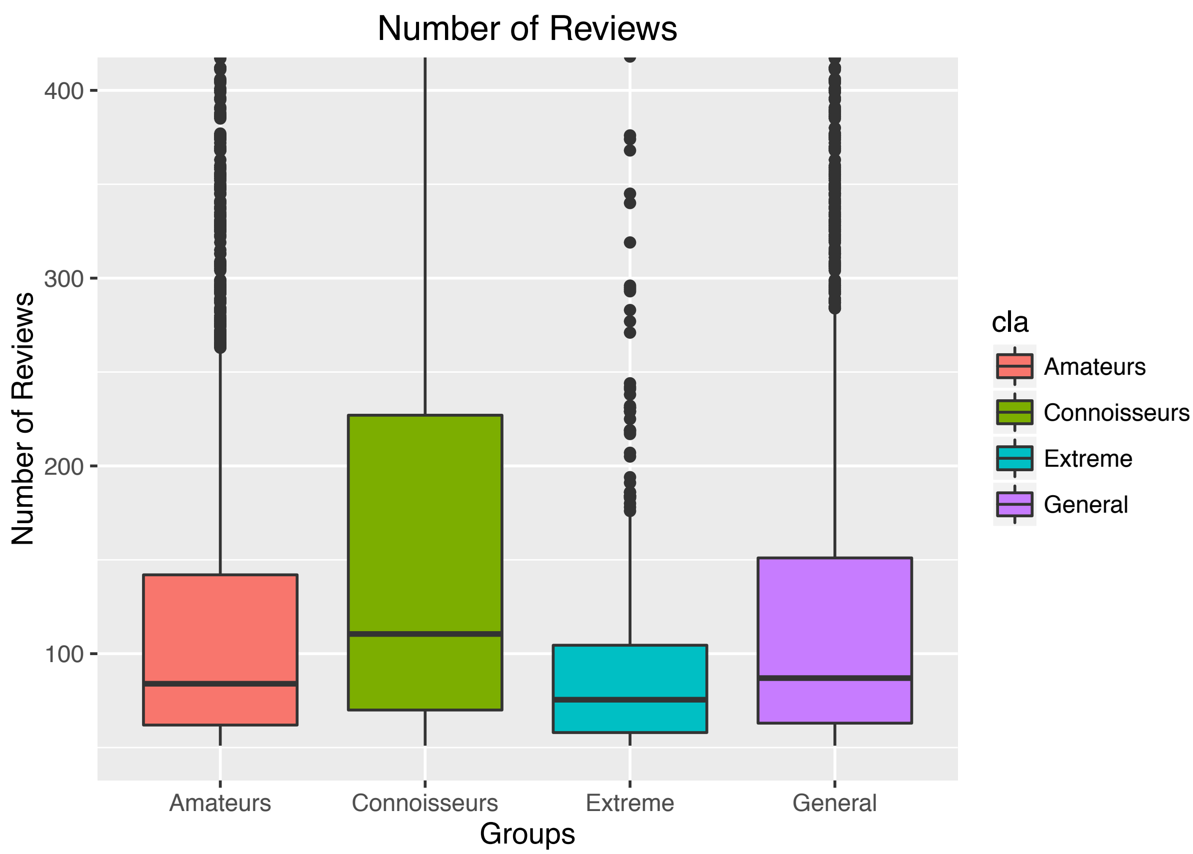
Add the number of words

```
connoi=left_join(connoi,word_for_user,by='review_userid')
ame=left_join(ame,word_for_user,by='review_userid')
extreme=left_join(extreme,word_for_user,by='review_userid')
user.table=left_join(user.table,word_for_user,by='review_userid')

con1=connoi
con1['cla']='Connoisseurs'
ame1=ame
ame1['cla']='Amateurs'
ext1=extreme
ext1['cla']='Extreme'
gen1=user.table
gen1['cla']='General'

whole=rbind(con1,ame1,ext1,gen1)
```

Comparasion between General, Connoisseurs, Amateurs and Extreme Case

Number of reviews

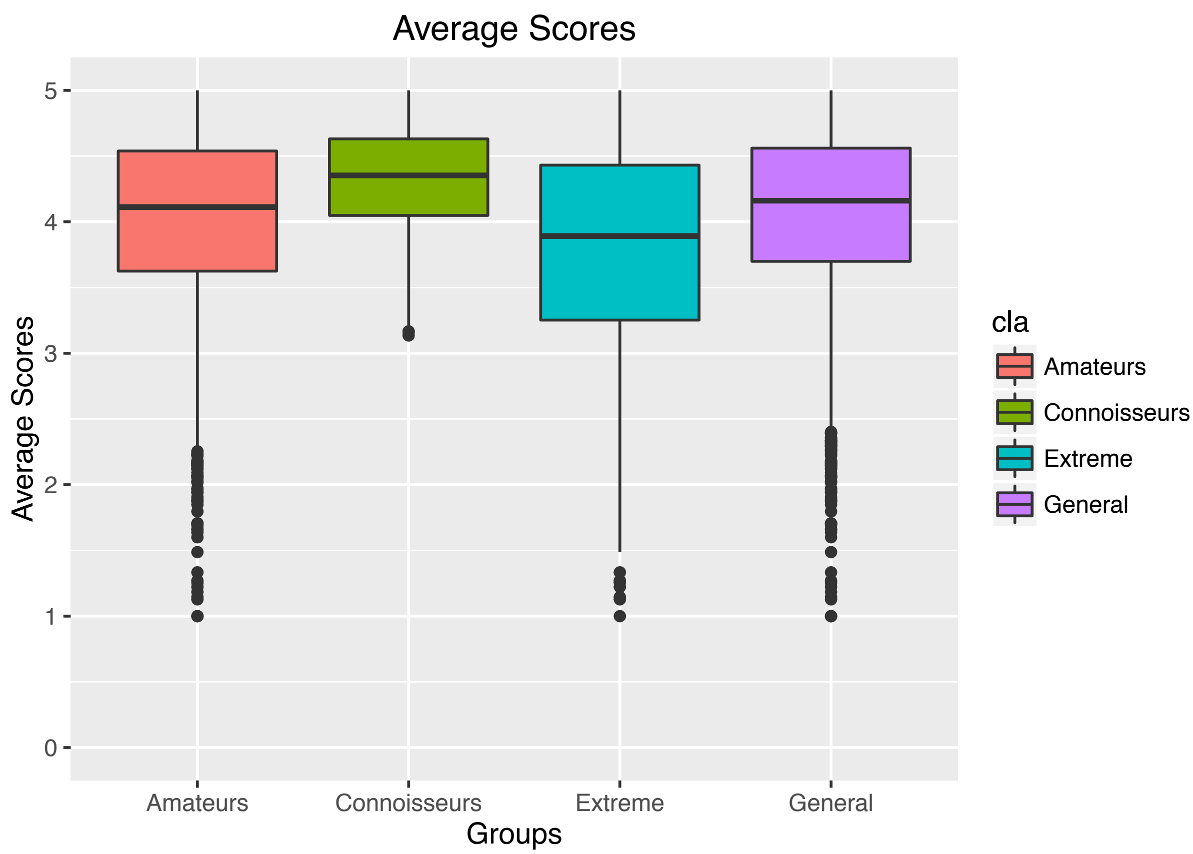
```
class=factor(whole$cla)
ggplot(whole,aes(cla,user.count))+geom_boxplot(aes(fill=cla))+coord_cartesian(ylim = c(50, 400))+
  xlab('Groups')+ylab('Number of Reviews')+ggtitle('Number of Reviews')
```




```
#par(mfrow=c(1,4))
#boxplot(connoi$user.count,ylim=c(0,200),main='Connoisseurs')
#boxplot(user.table$user.count,ylim=c(0,200),main='General')
#boxplot(ame$user.count,ylim=c(0,200),main='Amateurs')
```

Average score by individual

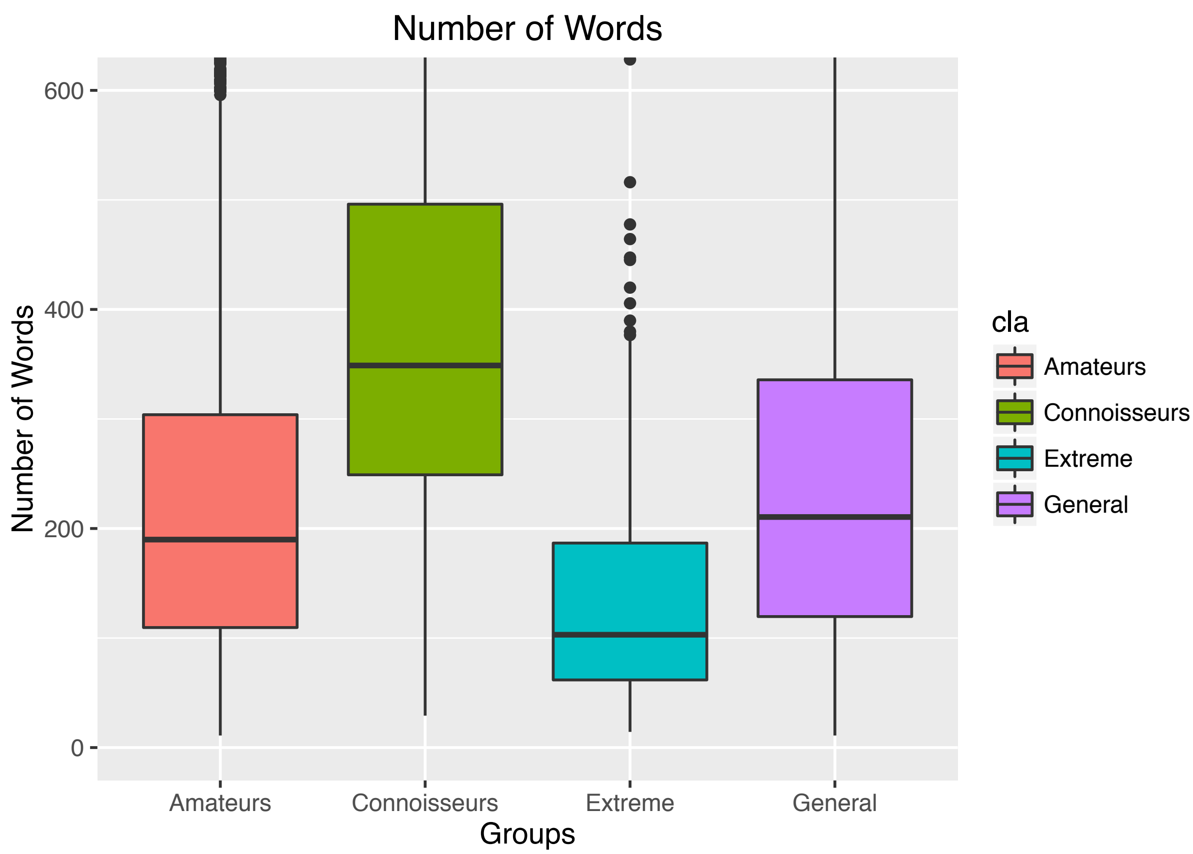
```
ggplot(whole,aes(cla,UReview_ave))+geom_boxplot(aes(fill=cla))+coord_cartesian(ylim = c(0, 5))+
  xlab('Groups')+ylab('Average Scores')+ggtitle('Average Scores')
```




```
#par(mfrow=c(1,3))
#boxplot(connoi$UReview_ave,main='Connoisseurs',ylim=c(0,5))
#boxplot(user.table$UReview_ave,main='General',ylim=c(0,5))
#boxplot(ame$UReview_ave,main='Amateurs',ylim=c(0,5))
#summary(connoi$UReview_ave)
#summary(user.table$UReview_ave)
```

Compare of the word_count

```
ggplot(whole,aes(cla,word_ave))+geom_boxplot(aes(fill=cla))+coord_cartesian(ylim = c(0, 600))+
  xlab('Groups')+ylab('Number of Words')+ggtitle('Number of Words')
```

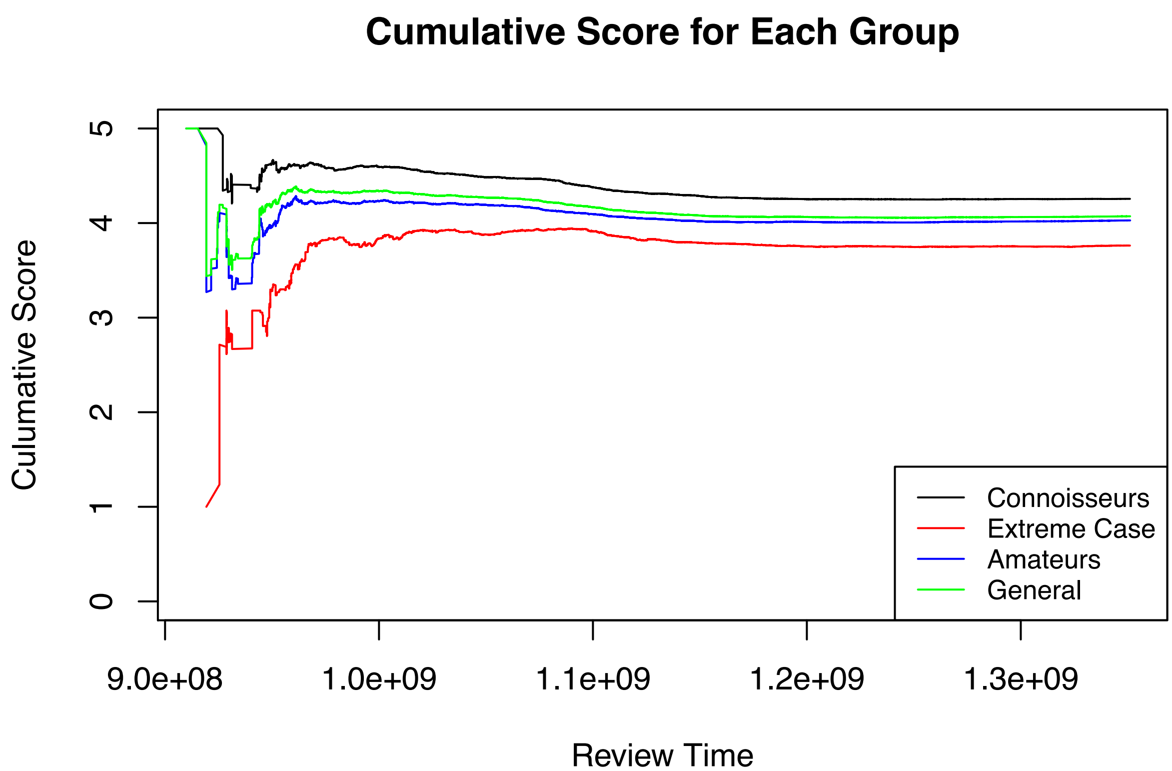



```r
#par(mfrow=c(1,3))
#boxplot(connoi$word_ave,main='Connoisseurs',ylim=c(0,600))
#boxplot(word_for_user$word_ave,main='General',ylim=c(0,600))
#boxplot(ame$word_ave,main='Amateurs',ylim=c(0,600))
```

Compare of the Cumulative Score

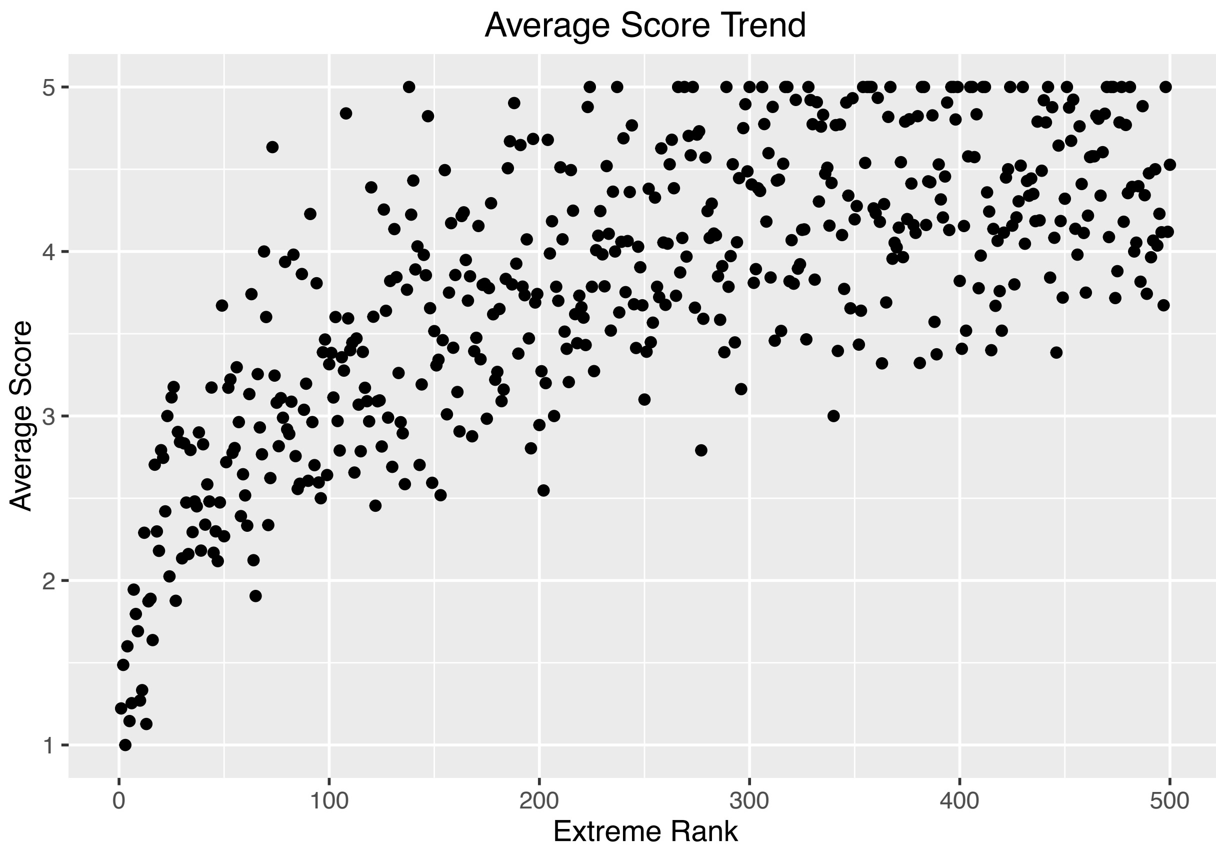
```r
par(mfrow=c(1,1))
# calculate the cumulative score for Connoisseurs
t.c=left_join(data_new,connoi,by='review_userid')
t.c1=filter(t.c,word_ave!='NA')

t.c1=t.c1[order(t.c1$review_time),]
x.c=t.c1$review_time
y.c=cumsum(t.c1$review_score)/seq_along(t.c1$review_score)


# calculate the cumulative score for Extreme Cases
t.e=left_join(data_new,extreme,by='review_userid')
t.e1=filter(t.e,word_ave!='NA')

t.e1=t.e1[order(t.e1$review_time),]
x.e=t.e1$review_time
```

```r
y.e=cumsum(t.e1$review_score)/seq_along(t.e1$review_score)


# calculate the cumulative score for Amateurs
t.a=left_join(data_new,ame,by='review_userid')
t.a1=filter(t.a,word_ave!='NA')

t.a1=t.a1[order(t.a1$review_time),]
x.a=t.a1$review_time
y.a=cumsum(t.a1$review_score)/seq_along(t.a1$review_score)

# calculate the cumulative score for General

t.g=data_new[order(data_new$review_time),]
x.g=t.g$review_time
y.g=cumsum(t.g$review_score)/seq_along(t.g$review_score)

plot(x.c,y.c,type='l',ylim=c(0,5),main='Cumulative Score for Each Group',xlab='Review Time',ylab = 'Cul
lines(x.e,y.e,col='red')
lines(x.a,y.a,col='blue')
lines(x.g,y.g,col='green')
legend('bottomright',legend=c('Connoisseurs','Extreme Case','Amateurs','General'),col=c('black','red','
```

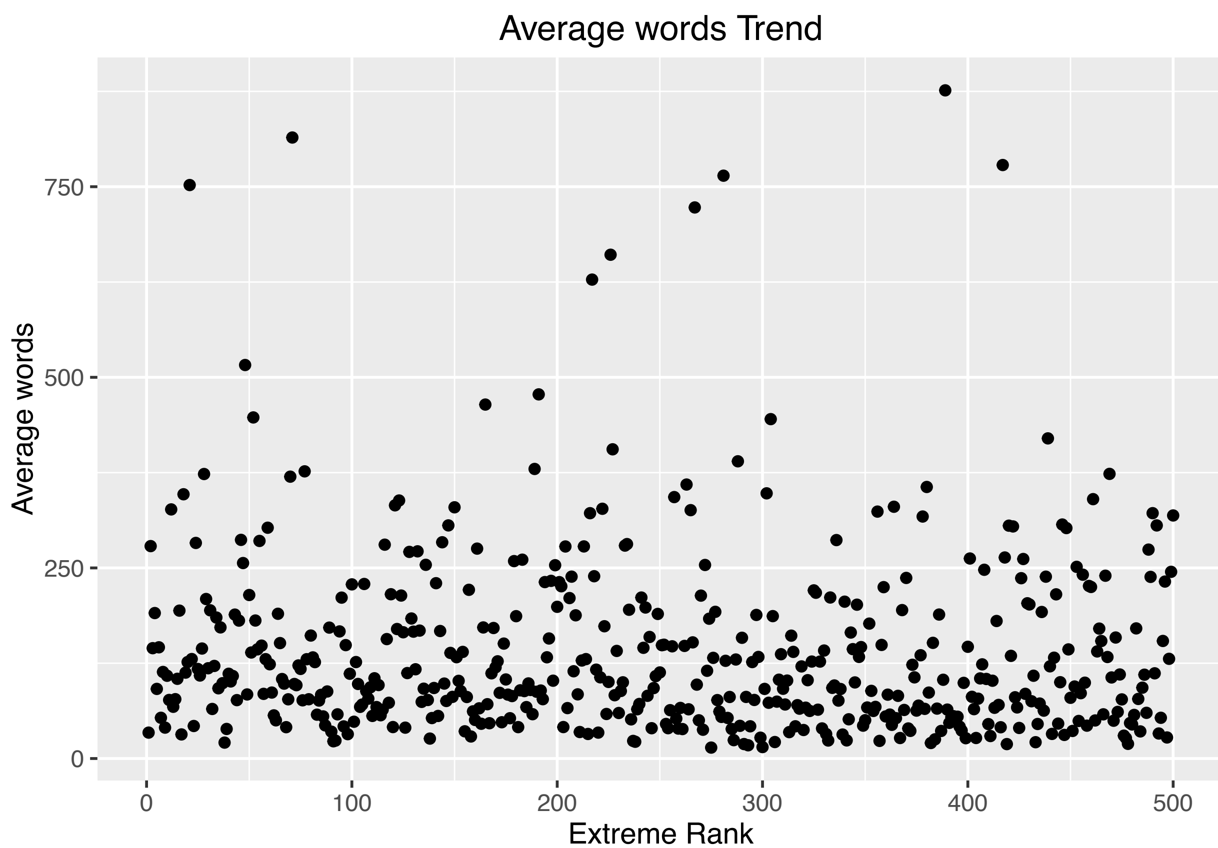



```r
#boxplot(extreme$user.count,ylim=c(1,200),main='Number of Reviews')
#boxplot(extreme$UReview_ave,ylim=c(0,5),main='Average Score')
```

```
x=seq(1:500)
y=extreme$UReview_ave
ggplot()+geom_point(aes(x,y))+ggtitle('Average Score Trend')+xlab('Extreme Rank')+ylab('Average Score')
```




```
y2=extreme$word_ave
ggplot()+geom_point(aes(x,y2))+ggtitle('Average words Trend')+xlab('Extreme Rank')+ylab('Average words'
```



Analysis of Expert

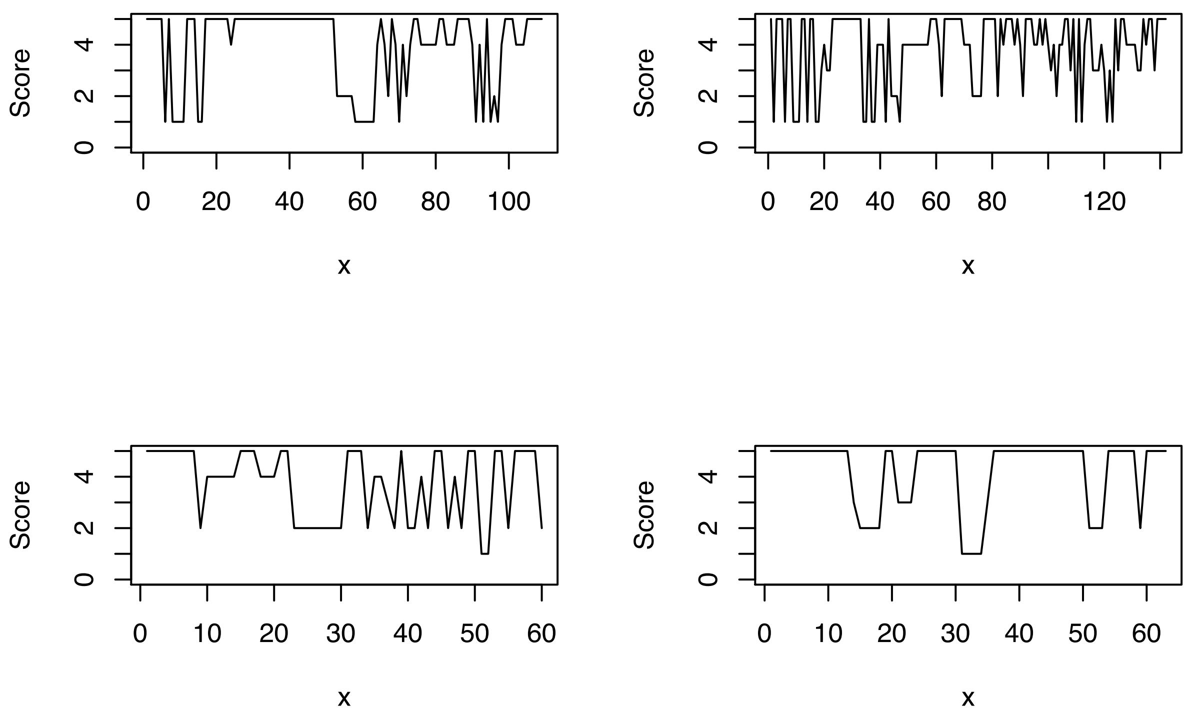
We also want to see the experts who have a good seperation of movies. Most of the experts have higher average score than the general. One reason for that is expert might more selective about movies that they only watch 'good' movies but this cause a problem of 'easy expert'. That is to say, it is easier to be an expert if you rate every movie high. In order to pick up experts who are critical, we calculate the sd of each individual expert of all the reviews they gave.

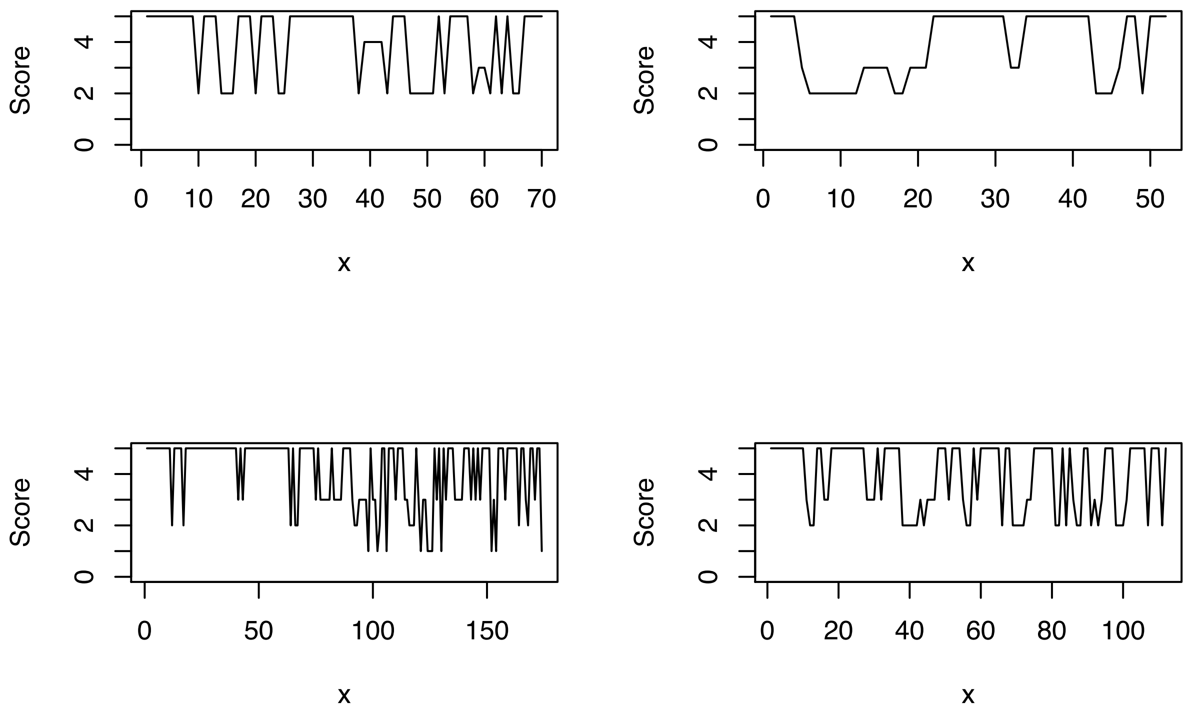
```
user.sd.new=data_new%>%
                group_by(review_userid)%>%
                summarize(
                  sd=sd(review_score,na.rm=T)
                )
connoi.new=left_join(connoi,user.sd.new,by='review_userid')
connoi.new=connoi.new[order(connoi.new$sd,decreasing = T),]
head(connoi.new)
```

```
## Source: local data frame [6 x 8]
##
##    review_userid user.count UReview_ave UReview_read UReview_help
##            (chr)      (int)       (dbl)        (dbl)        (dbl)
## 1 A37JKM7EFD0DIQ        109    3.935780     5.045872    0.6264788
## 2 A10BPHRXHZF8P6        142    3.816901     6.260563    0.6069659
## 3 A298JV8C4ADLU7         60    3.733333     5.083333    0.6480769
```

```
## 4 A25QXIFEHR6900         63    4.206349    35.587302    0.7333848
## 5  AZ9JWGE1UGKZA         70    4.028571    15.371429    0.7577461
## 6 A38U7Z88Q1MDWL         52    3.826923     6.000000    0.7392872
## Variables not shown: sd_total (dbl), word_ave (dbl), sd (dbl)
```

```r
critical=connoi.new[1:20,]
par(mfrow=c(2,2))
for (i in 1:8){
user=critical$review_userid[i]
user.temp=filter(data_new,review_userid==user)
x=seq(1:nrow(user.temp))
y=user.temp$review_score
plot(x,y,type='l',ylim=c(0,5),ylab='Score')
}
```





From the above plots we can see that ‘critical’ expert really have a clear seperation of scores. Some of the experts simply give ‘good’ movies 5 scores and ‘bad’ movies 1 score.

Sentimental Analysis

Yuhan Sun

April 11, 2016

Main reference: Sentimental Analysis in R Main Corpus: AFINN wordlist (http://www2.imm.dtu.dk/pubdb/views/publication_details.php?id=6010), Useful Adjectives for Describing Movies(http://member.tokoha-u.ac.jp/~dixonfdm/Writing%20Topics%20htm/Movie%20Review%20Folder/movie_descrip_vocab.htm)

Prepare the corpus

```
setwd('/Users/sunxiaohan/Desktop/project4/Sentiment')
afinn_list <- read.delim(file='AFINN/AFINN-111.txt', header=FALSE, stringsAsFactors=FALSE)
names(afinn_list) <- c('word', 'score')
afinn_list$word <- tolower(afinn_list$word)
#categorize words as very negative to very positive and add some movie-specific words
vNegTerms <- afinn_list$word[afinn_list$score==-5 | afinn_list$score==-4]

negTerms <- c(afinn_list$word[afinn_list$score==-3 | afinn_list$score==-2 | afinn_list$score==-1], "sec

posTerms <- c(afinn_list$word[afinn_list$score==3 | afinn_list$score==2 | afinn_list$score==1], "first-

vPosTerms <- c(afinn_list$word[afinn_list$score==5 | afinn_list$score==4], "uproarious", "riveting", "f
```

Sentiment Analysis function

```
library(plyr)
#function to calculate number of words in each category within a sentence
sentimentScore <- function(sentences, vNegTerms, negTerms, posTerms, vPosTerms){
  final_scores <- matrix('', 0, 5)
  scores <- laply(sentences, function(sentence, vNegTerms, negTerms, posTerms, vPosTerms){
    initial_sentence <- sentence
    #remove unnecessary characters and split up by word
    sentence <- gsub('[[:punct:]]', '', sentence)
    sentence <- gsub('[[:cntrl:]]', '', sentence)
    sentence <- gsub('\\d+', '', sentence)
    sentence <- tolower(sentence)
    wordList <- str_split(sentence, '\\s+')
    words <- unlist(wordList)
    #build vector with matches between sentence and each category
    vPosMatches <- match(words, vPosTerms)
    posMatches <- match(words, posTerms)
    vNegMatches <- match(words, vNegTerms)
    negMatches <- match(words, negTerms)
    #sum up number of words in each category
    vPosMatches <- sum(!is.na(vPosMatches))
```

```
    posMatches <- sum(!is.na(posMatches))
    vNegMatches <- sum(!is.na(vNegMatches))
    negMatches <- sum(!is.na(negMatches))
    score <- c(vNegMatches, negMatches, posMatches, vPosMatches)
    #add row to scores table
    newrow <- c(initial_sentence, score)
    final_scores <- rbind(final_scores, newrow)
    return(final_scores)
  }, vNegTerms, negTerms, posTerms, vPosTerms)
  return(scores)
 }
```

load the original text data

```
library(stringr)
library(dplyr)
```

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

## The following objects are masked from 'package:plyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize

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

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

```
load("/Users/sunxiaohan/Desktop/project4/connoi.Rdata")
data_use=readRDS('/Users/sunxiaohan/Desktop/project4/data_use.RDS')
load("/Users/sunxiaohan/Desktop/project4/extreme.Rdata")

# CON
Result.score.co=matrix(ncol=5,nrow=500)
colnames(Result.score.co) <- c('vNeg', 'neg', 'pos', 'vPos','Total')
for (i in 1:nrow(Result.score.co)){
  con.name=connoi$review_userid[i]
  text.raw=filter(data_use,review_userid==con.name)
  nr=nrow(text.raw)
  text.do=text.raw$review_text
  text=unlist(lapply(text.do, function(x) { str_split(x, "\n") }))
  Result <- as.data.frame(sentimentScore(text, vNegTerms, negTerms, posTerms, vPosTerms))
  Result1=Result[,2:5]
  for (a in 1:4){
```

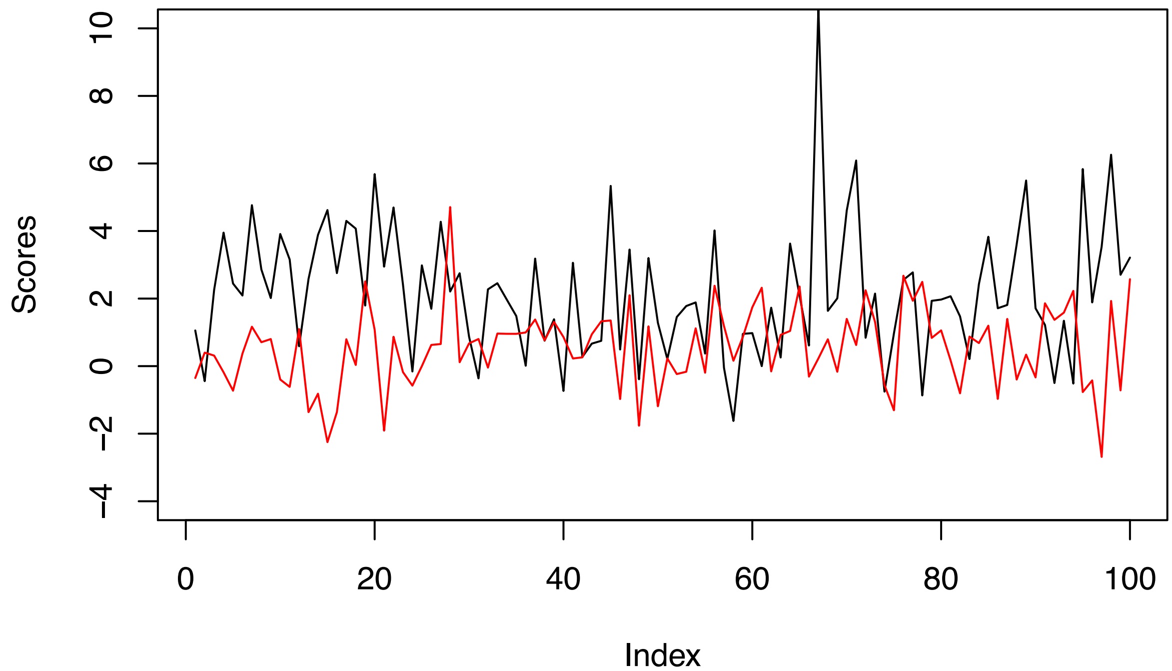
```r
    Result.score.co[i,a]=sum(as.numeric(Result1[,a])-1)/nr
  }
  Result.score.co[i,5]=2*Result.score.co[i,4]+Result.score.co[i,3]-Result.score.co[i,2]-2*Result.score.c
}
head(Result.score.co)
```

```
##             vNeg       neg      pos      vPos      Total
## [1,] 0.00000000 0.3943662 1.450704 0.0000000  1.0563380
## [2,] 0.33333333 0.9259259 1.148148 0.0000000 -0.4444444
## [3,] 0.00000000 1.2586207 1.724138 0.8965517  2.2586207
## [4,] 0.00000000 1.2619048 3.000000 1.1071429  3.9523810
## [5,] 0.00000000 0.2407407 1.240741 0.7222222  2.4444444
## [6,] 0.09090909 2.5363636 2.318182 1.2454545  2.0909091
```

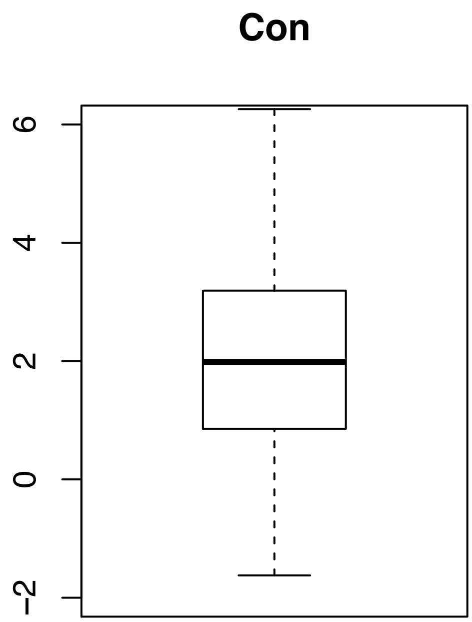
```r
# Extreme Case
Result.score.ex=matrix(ncol=5,nrow=500)
colnames(Result.score.ex) <- c('vNeg', 'neg', 'pos', 'vPos','Total')
for (i in 1:nrow(Result.score.ex)){
  ex.name=extreme$review_userid[i]
  text.raw=filter(data_use,review_userid==ex.name)
  nr=nrow(text.raw)
  text.do=text.raw$review_text
  text=unlist(lapply(text.do, function(x) { str_split(x, "\n") }))
  Result <- as.data.frame(sentimentScore(text, vNegTerms, negTerms, posTerms, vPosTerms))
  Result1=Result[,2:5]
  for (a in 1:4){
    Result.score.ex[i,a]=sum(as.numeric(Result1[,a])-1)/nr
  }
  Result.score.ex[i,5]=2*Result.score.ex[i,4]+Result.score.ex[i,3]-Result.score.ex[i,2]-2*Result.score.e
}
head(Result.score.ex)
```

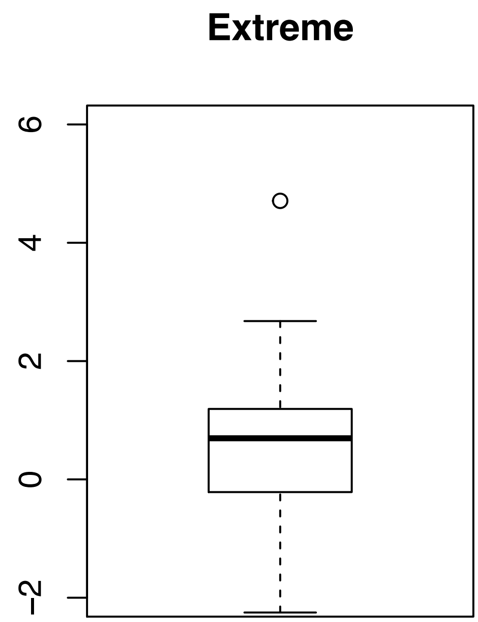
```
##           vNeg      neg       pos       vPos      Total
## [1,] 0.0000000 1.333333 0.9444444 0.01851852 -0.3518519
## [2,] 0.0000000 5.469565 4.3043478 0.78260870  0.4000000
## [3,] 0.6229508 1.000000 1.4426230 0.55737705  0.3114754
## [4,] 0.1333333 2.800000 2.5166667 0.18333333 -0.1833333
## [5,] 0.0000000 1.472727 0.7454545 0.00000000 -0.7272727
## [6,] 0.0000000 1.661017 1.2881356 0.37288136  0.3728814
```

```r
x1=Result.score.co[1:100,5]
plot(x1,type='l',ylim=c(-4,10),ylab='Scores')
x2=Result.score.ex[1:100,5]
lines(x2,col='red')
```




```
par(mfrow=c(1,2))
boxplot(x1,ylim=c(-2,6),main='Con')
boxplot(x2,ylim=c(-2,6),main='Extreme')
```


Con
6
4
2
0
−2


Extreme
6
4
2
0
−2

Experts Recommendation

Jadie Zuo

April 11, 2016

Data Preparetion

We selecte the most deviated users: 100 most deviated reviewers, and 100 experts.

```
con <- load("connoi.RData")
ext <- load("extreme.RData")
mydata <- readRDS("users_50_products_100.RDS")
exp <- connoi[1:100,]
ext <- extreme[1:100,]
colnames(exp) <- c("userid","review_num","review_ave","help_num","help_score","dev")
colnames(ext) <- c("userid","review_num","review_ave","help_num","help_score","dev")
```

Prepare the node dataset: a 200 by 9 matrix with rows being the combination of the most deviated reviewrs and experts, and columns being the following features: * ID: identification number (a sequence from 1 to 200)
* userid: ID assigned by Amazon
* review_num: number of reviews created
* review_ave: average score of review
* help_num: number of helpfulness reviews by other users
* help_score: helpfulness score evaluated by other users
* dev: expertise measurement that is calculated by the deviation from his average review score to the overall review score
* type: binary variable with 1 being deviated reviewers and 2 being experts
* type.label: labels for type, extreme reviewers and experts

```
a <- load("node.RData")
node$type <- c(rep(1,100), rep(2,100))
node$type.label <- c(rep("Extreme Reviewers",100), rep("Experts",100))
node <- cbind(seq(1,200,1),node)
```

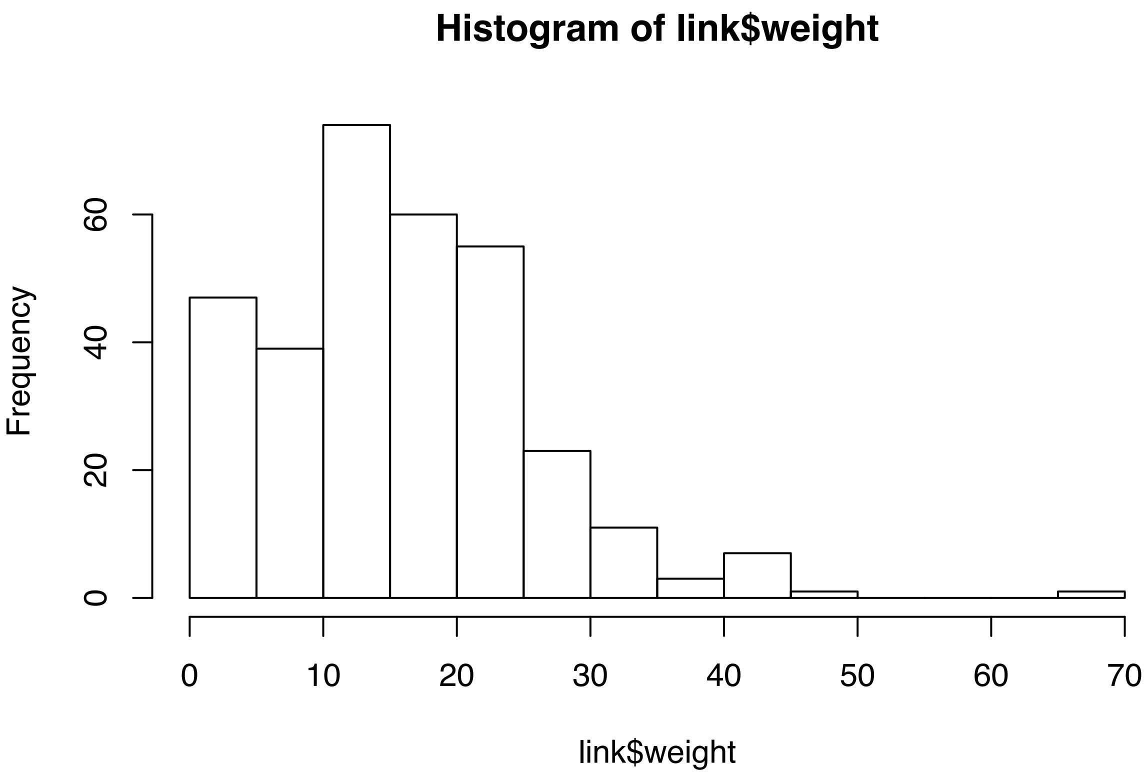
Prepare the edge dataset: a 321 by 4 matrix with rows being edges among 200 reviewers and following column factors:
* from: start point of an edge
* to: end point of an edge
* weight: number of movies that two nodes have commonly seen
* type: how strong the connection is, with 1 being the weight below 10 indicating a weak connection, 2 being the weight between 10 and 25 indicating a connection, 3 being weight above 25 indicating strong connection.

```
con <- matrix(nrow = 100,ncol = 100)
for (i in 1:100) {
  one <- mydata[which(mydata$review_userid == ext$review_userid[i]),]
  x1 = as.numeric(unique(one$product_productid))
  for (j in 1:100) {
    two <- mydata[which(mydata$review_userid == exp$review_userid[j]),]
    y1 = as.numeric(unique(two$product_productid))
    count <- length(intersect(x1, y1))
    con[i,j] <- count
```

```
  }
}

from <- c(1,1,1,1,1,2,2,2,2,3,3,3,3,3,4,5,6,6,6,6,6,6,6,6,7,7,9,9,9,9,9,9,9,9,
          9,10,10,10,10,10,10,10,11,11,11,11,11,11,11,13,13,13,13,13,13,14,
          14,14,15,16,16,16,17,17,18,18,19,19,19,20,20,21,21,21,21,22,26,26,
          26,26,26,26,27,27,28,28,28,29,29,29,29,29,29,30,32,32,32,34,34,35,
          35,35,36,36,37,37,38,38,38,38,38,38,38,38,39,39,39,39,41,41,42,42,
          42,42,42,42,42,42,43,43,43,43,43,44,44,45,45,45,45,46,46,46,46,46,
          46,46,46,46,47,47,47,49,49,49,49,49,49,50,50,50,50,50,50,50,50,50,
          50,50,50,51,51,52,52,52,54,54,54,54,54,54,54,54,55,55,56,56,56,56,
          57,57,57,57,58,58,58,59,60,60,60,61,62,63,64,64,64,64,64,66,67,67,
          68,68,69,70,70,70,70,71,71,72,72,72,72,72,72,72,72,72,73,73,73,73,
          73,74,74,76,76,76,77,77,77,78,78,78,78,79,79,80,80,80,80,81,81,81,
          81,82,82,82,82,83,83,84,84,84,84,84,84,85,85,85,86,86,87,87,87,87,
          88,89,89,89,89,89,89,90,90,91,91,91,91,92,92,92,92,93,94,94,95,96,
          96,96,96,96,96,97,98,98,98,98,98,98,98,99,99,99,99,99,99,99,100,
          100,100,100)
to <- c(34,64,82,83,95,67,75,79,83,15,35,72,94,52,92,27,30,43,59,72,6,14,57,
        11,93,22,32,54,92,94,75,76,83,67,29,67,43,64,92,83,95,83,92,70,73,86,
        87,63,90,43,92,67,75,64,99,90,93,75,50,32,75,90,93,68,61,83,91,92,64,
        17,12,92,96,90,63,40,92,61,24,54,83,70,90,66,83,92,8,14,43,59,83,100,
        29,68,90,97,83,91,83,56,43,90,75,47,83,1,32,54,67,94,90,98,92,83,92,
        75,63,21,92,55,68,82,28,75,90,22,99,16,43,64,92,100,92,67,90,75,92,42,
        93,44,58,63,39,75,89,32,92,35,92,4,38,59,60,83,20,92,95,65,99,62,10,
        67,73,56,75,92,91,90,83,53,90,83,91,53,59,43,83,88,56,75,92,48,92,56,
        75,19,63,48,49,75,83,91,90,93,85,9,26,83,65,83,99,82,43,21,75,90,91,49,
        64,83,100,83,92,67,53,75,83,90,83,8,19,42,43,64,91,92,100,68,62,6,14,
        57,47,83,90,92,32,98,82,53,91,90,83,82,83,90,41,66,32,83,53,93,90,85,
        78,62,83,55,92,90,70,12,44,75,92,45,35,72,94,83,55,68,83,24,54,53,48,
        41,75,43,19,63,56,50,39,40,43,92,92,49,75,83,79,82,92,96,73,59,69,56,
        75,92,75,64,4,63,70,73,86,87,85,90,83,34,44,92,95,11,1,42,92)
weight <- c()
for (i in 1:321){
  weight[i] <- con[from[i],to[i]]
}
```

Take a look at how “weight” is distributed:

```
hist(link$weight)
```



Creat a categorical varaible using the weight variable to describe the level of similarity between reviewers. According to the histogram, use 10 and 25 as two cut off points:

```
type <- c()
for (i in 1:321){
  if (weight[i] < 10) {
    temp <- 1
  }
  else if (weight[i] < 25) {
    temp <- 2
  }
  else {
    temp <- 3
  }
  type[i] <- temp
}
link <- data.frame(from,to,weight,type)
colnames(link) <- c("from", "to", "weight", "type")
rownames(link) <- NULL
```

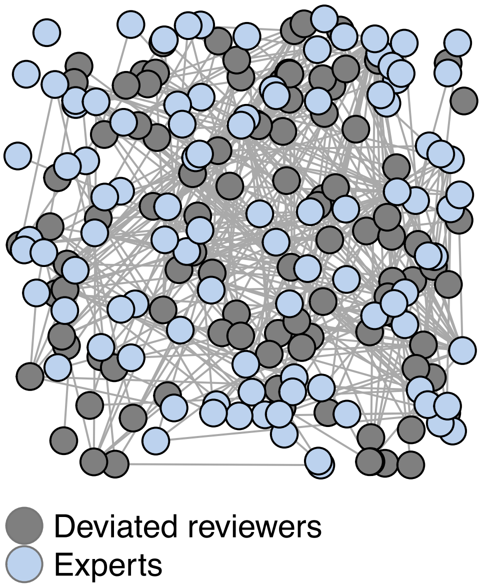
Network Plots

Network layout using igraph:

```
library(igraph)
library(RColorBrewer)
net <- graph.data.frame(link, node, directed=T)
net <- simplify(net, remove.multiple = F, remove.loops = T)
colrs <- c("gray50", "lightsteelblue2")
```

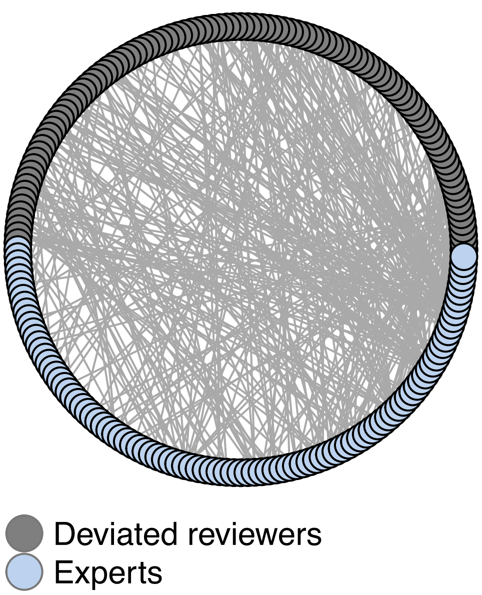
Random Network Layout

```
plot(net, vertex.size=12, edge.arrow.size=0, edge.curved=0,vertex.color=colrs[V(net)$type],
     vertex.frame.color="black",vertex.label=NA, layout=layout.random)
legend(x=-1.1, y=-1.1, c("Deviated reviewers","Experts"), pch=21,
       col="#777777", pt.bg=colrs, pt.cex=2.5, bty="n", ncol=1)
```



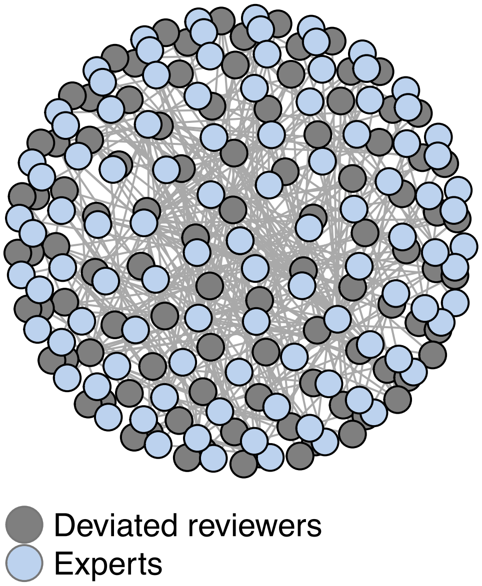
Circle Layout

```
plot(net,vertex.size=12, edge.arrow.size=0, edge.curved=0,vertex.color=colrs[V(net)$type],
     vertex.frame.color="black",vertex.label=NA,layout=layout.circle(net))
legend(x=-1.1, y=-1.1, c("Deviated reviewers","Experts"), pch=21,
       col="#777777", pt.bg=colrs, pt.cex=2.5, bty="n", ncol=1)
```



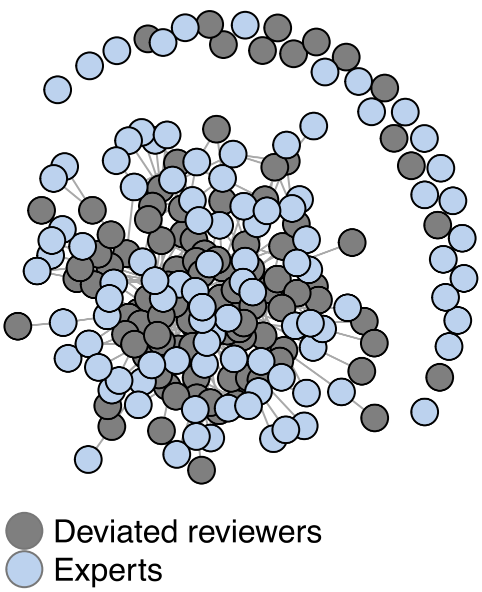
3D sphere layout:

```
plot(net,vertex.size=12, edge.arrow.size=0, edge.curved=0,vertex.color=colrs[V(net)$type],
     vertex.frame.color="black",vertex.label=NA,layout=layout.sphere(net))
legend(x=-1.1, y=-1.1, c("Deviated reviewers","Experts"), pch=21,
       col="#777777", pt.bg=colrs, pt.cex=2.5, bty="n", ncol=1)
```



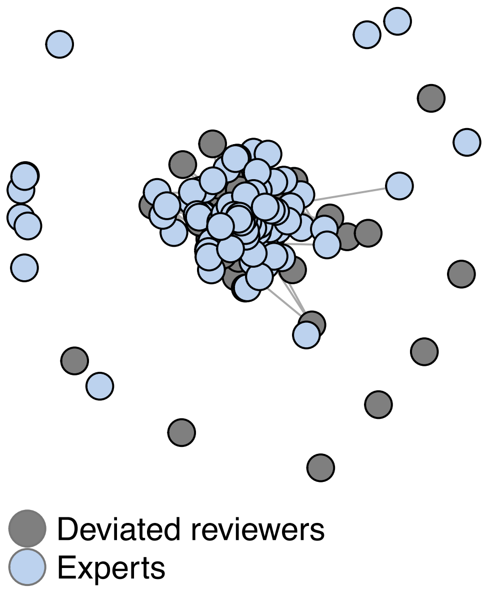
The Fruchterman-Reingold force-directed algorithm:

```
plot(net,vertex.size=12, edge.arrow.size=0, edge.curved=0,vertex.color=colrs[V(net)$type],
     vertex.frame.color="black",vertex.label=NA,layout=layout.fruchterman.reingold)
legend(x=-1.1, y=-1.1, c("Deviated reviewers","Experts"), pch=21,
       col="#777777", pt.bg=colrs, pt.cex=2.5, bty="n", ncol=1)
```



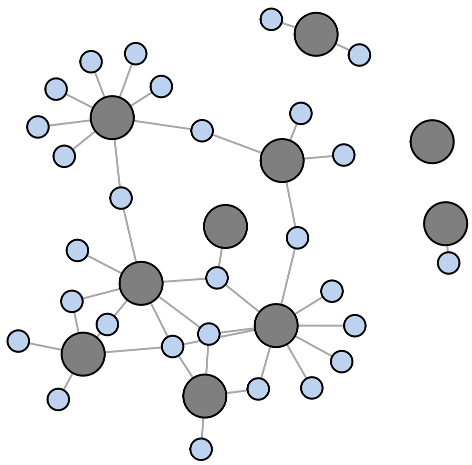
The Kamada Kawai forced-directed algorithm:

```r
plot(net,vertex.size=12, edge.arrow.size=0, edge.curved=0,vertex.color=colrs[V(net)$type],
     vertex.frame.color="black",vertex.label=NA,layout=layout.kamada.kawai(net))
legend(x=-1.1, y=-1.1, c("Deviated reviewers","Experts"), pch=21,
       col="#777777", pt.bg=colrs, pt.cex=2.5, bty="n", ncol=1)
```

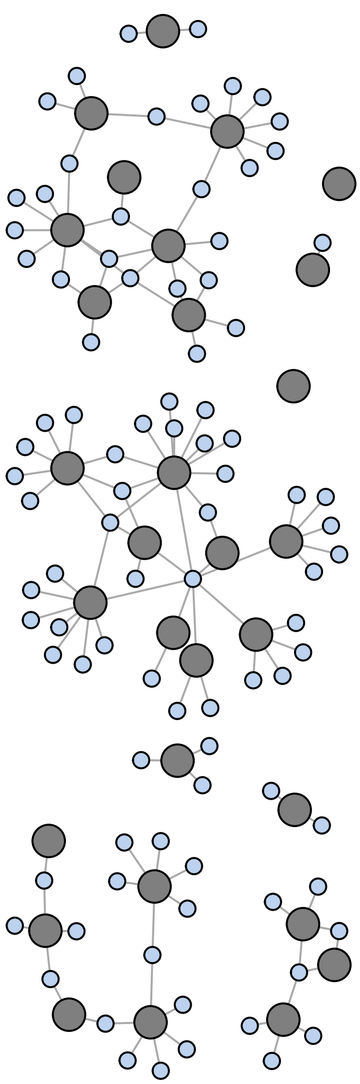


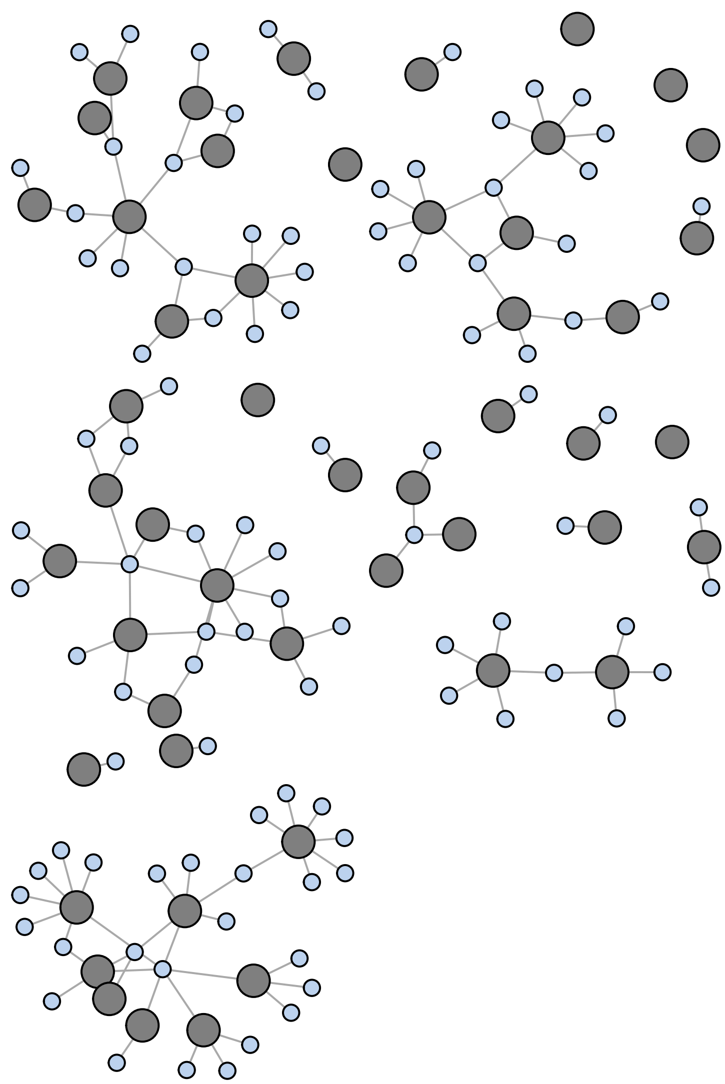
Connect experts with the needed (10 deviated reviewers)

```r
colrs <- c("gray50", "lightsteelblue2")
node.new <- node[c(1:10,101:200),]
link.new <- link[which(link$from < 11),]
node.new <- node[c(1:10,unique(link.new$to)),]
net.new <- graph.data.frame(link.new, node.new, directed=T)
net.new <- simplify(net.new, remove.multiple = F, remove.loops = T)
l <- layout.fruchterman.reingold(net.new, repulserad=vcount(net.new)^3,
                                        area=vcount(net.new)^2.4)
plot(net.new, vertex.size=20/V(net.new)$type, edge.arrow.size=0, edge.curved=0,
     vertex.color=colrs[V(net.new)$type], vertex.frame.color="black",
     vertex.label=NA, layout=l)
```



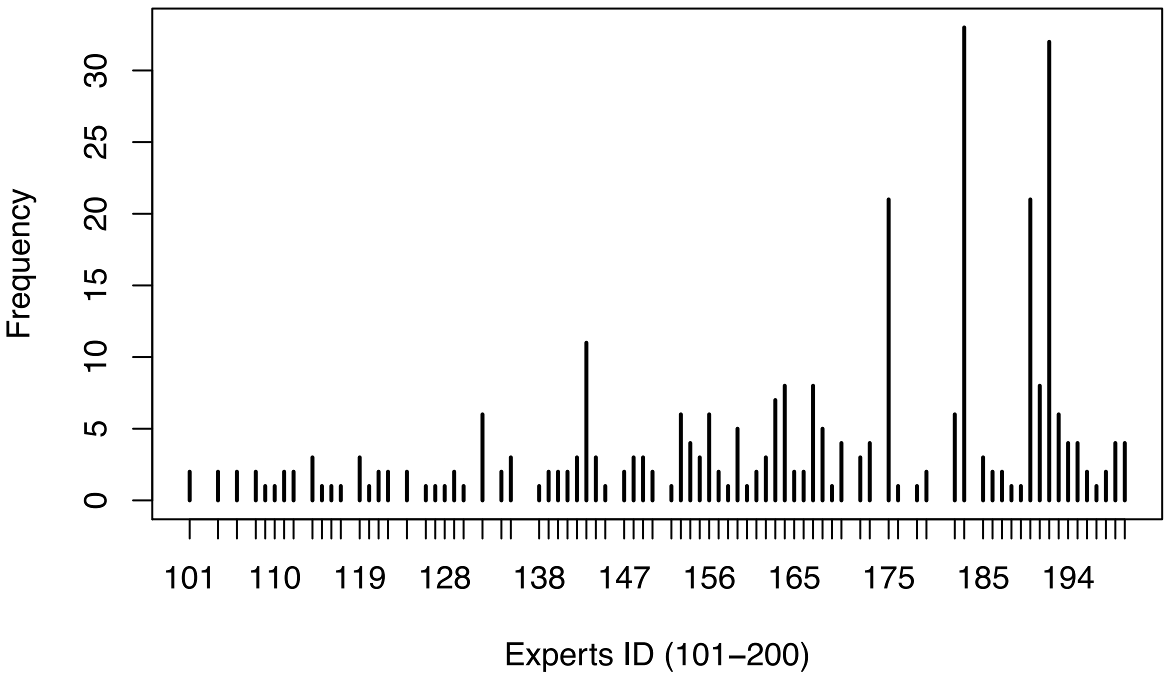
Expert recommendation for all the deviated users:





Exam the involvement of experts in the system:

```r
plot(table(link$to),xlab="Experts ID (101-200)", ylab="Frequency")
```




```r
length(order(table(link$to)))
```

```
## [1] 80
```

```r
#There are 80 experts out of 100 recommended to the deviated reviewers.
#Print 10 most advanced expters
table(link$to)[order(table(link$to))[71:80]]
```

```
##
## 193 163 164 167 191 143 175 190 192 183
##   6   7   8   8   8  11  21  21  32  33
```

Who are they?

```r
adv <- exp[c(93,63,64,67,91,43,75,90,92,83),c(2:6)]
adv
```

```
##    review_num review_ave  help_num help_score       dev
## 93         96   4.416667  7.375000  0.7293581 0.3307292
## 63        223   4.654709 17.699552  0.7539035 0.2780722
## 64         70   4.371429 14.600000  0.7800065 0.2793805
## 67        238   4.689076 35.180672  0.8531945 0.2890479
## 91         64   4.609375 12.078125  0.8715278 0.3287300
## 43         54   4.333333 11.333333  0.9220779 0.2384003
## 75         64   4.718750 10.031250  0.7560153 0.3021759
## 90         59   4.440678 28.474576  0.7509383 0.3286450
## 92        406   4.349754 20.460591  0.7909175 0.3297312
## 83         76   4.197368  7.855263  0.8715479 0.3152513
```

```r
colMeans(adv)
```

```
##  review_num  review_ave    help_num  help_score         dev
## 135.0000000   4.4781138  16.5088363   0.8079487   0.3020163
```

```r
exp_sub <- exp[,c(2:6)]
colMeans(exp_sub)
```

```
##  review_num  review_ave    help_num  help_score         dev
## 125.9300000   4.5914989  15.6489400   0.8000546   0.2402854
```

1. Average number of reviews for movies is considerable high than the experts popylation
   —> No surprise

2. Average review scores for the 10 advanced experts is lower than the experts population
   —> More critical?

3. Deviation of the 10 advanced experts is higher than the experts population
   —> Professional perspective?