Group_project

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Summary

Introduction

Loading and Exploring Data

Libraries required

Data size and structure

```
df.train <- read_csv("~/Documents/HKU/SOWK3136/SOWK3136_grp_proj/dataset/dreaddit-train.csv")
df.test <- read_csv("~/Documents/HKU/SOWK3136/SOWK3136_grp_proj/dataset/dreaddit-test.csv")

df.full  <- bind_rows(df.train, df.test)
```

```
dim(df.full)
```

```
## [1] 3553  116
```

```
str(df.full[,c(1:10)])
```

```
## tibble [3,553 x 10] (S3: tbl_df/tbl/data.frame)
##  $ subreddit       : chr [1:3553] "ptsd" "assistance" "ptsd" "relationships" ...
##  $ post_id         : chr [1:3553] "8601tu" "8lbrx9" "9ch1zh" "7rorpp" ...
##  $ sentence_range  : chr [1:3553] "(15, 20)" "(0, 5)" "(15, 20)" "[5, 10]" ...
##  $ text            : chr [1:3553] "He said he had not felt that way before, suggeted I go rest and so
##  $ id              : num [1:3553] 33181 2606 38816 239 1421 ...
##  $ label           : num [1:3553] 1 0 1 1 1 1 0 1 1 1 ...
##  $ confidence      : num [1:3553] 0.8 1 0.8 0.6 0.8 1 0.8 0.8 0.6 1 ...
##  $ social_timestamp: num [1:3553] 1.52e+09 1.53e+09 1.54e+09 1.52e+09 1.54e+09 ...
##  $ social_karma    : num [1:3553] 5 4 2 0 24 2 6 1 134 20 ...
##  $ syntax_ari      : num [1:3553] 1.81 9.43 7.77 2.67 7.55 ...
```

Missing data, label encoding, and factorizing variables

```r
sum(is.na(df.full))
```

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

```r
apply(apply(df.full,2,is.na),2,sum) ; nrow(df.full)
```

```
##            subreddit               post_id        sentence_range
##                    0                     0                     0
##                 text                    id                 label
##                    0                     0                     0
##           confidence      social_timestamp          social_karma
##                    0                     0                     0
##           syntax_ari            lex_liwc_WC      lex_liwc_Analytic
##                    0                     0                     0
##       lex_liwc_Clout     lex_liwc_Authentic         lex_liwc_Tone
##                    0                     0                     0
##         lex_liwc_WPS        lex_liwc_Sixltr          lex_liwc_Dic
##                    0                     0                     0
##    lex_liwc_function      lex_liwc_pronoun        lex_liwc_ppron
##                    0                     0                     0
##           lex_liwc_i           lex_liwc_we          lex_liwc_you
##                    0                     0                     0
##       lex_liwc_shehe         lex_liwc_they        lex_liwc_ipron
##                    0                     0                     0
##     lex_liwc_article         lex_liwc_prep      lex_liwc_auxverb
##                    0                     0                     0
##      lex_liwc_adverb         lex_liwc_conj       lex_liwc_negate
##                    0                     0                     0
##        lex_liwc_verb          lex_liwc_adj      lex_liwc_compare
##                    0                     0                     0
##    lex_liwc_interrog       lex_liwc_number        lex_liwc_quant
##                    0                     0                     0
##      lex_liwc_affect       lex_liwc_posemo       lex_liwc_negemo
##                    0                     0                     0
##         lex_liwc_anx        lex_liwc_anger          lex_liwc_sad
##                    0                     0                     0
##      lex_liwc_social       lex_liwc_family       lex_liwc_friend
##                    0                     0                     0
##      lex_liwc_female         lex_liwc_male      lex_liwc_cogproc
##                    0                     0                     0
##     lex_liwc_insight        lex_liwc_cause      lex_liwc_discrep
##                    0                     0                     0
##      lex_liwc_tentat      lex_liwc_certain       lex_liwc_differ
##                    0                     0                     0
##     lex_liwc_percept          lex_liwc_see         lex_liwc_hear
##                    0                     0                     0
##        lex_liwc_feel          lex_liwc_bio         lex_liwc_body
##                    0                     0                     0
##      lex_liwc_health       lex_liwc_sexual       lex_liwc_ingest
##                    0                     0                     0
##      lex_liwc_drives   lex_liwc_affiliation      lex_liwc_achieve
##                    0                     0                     0
```

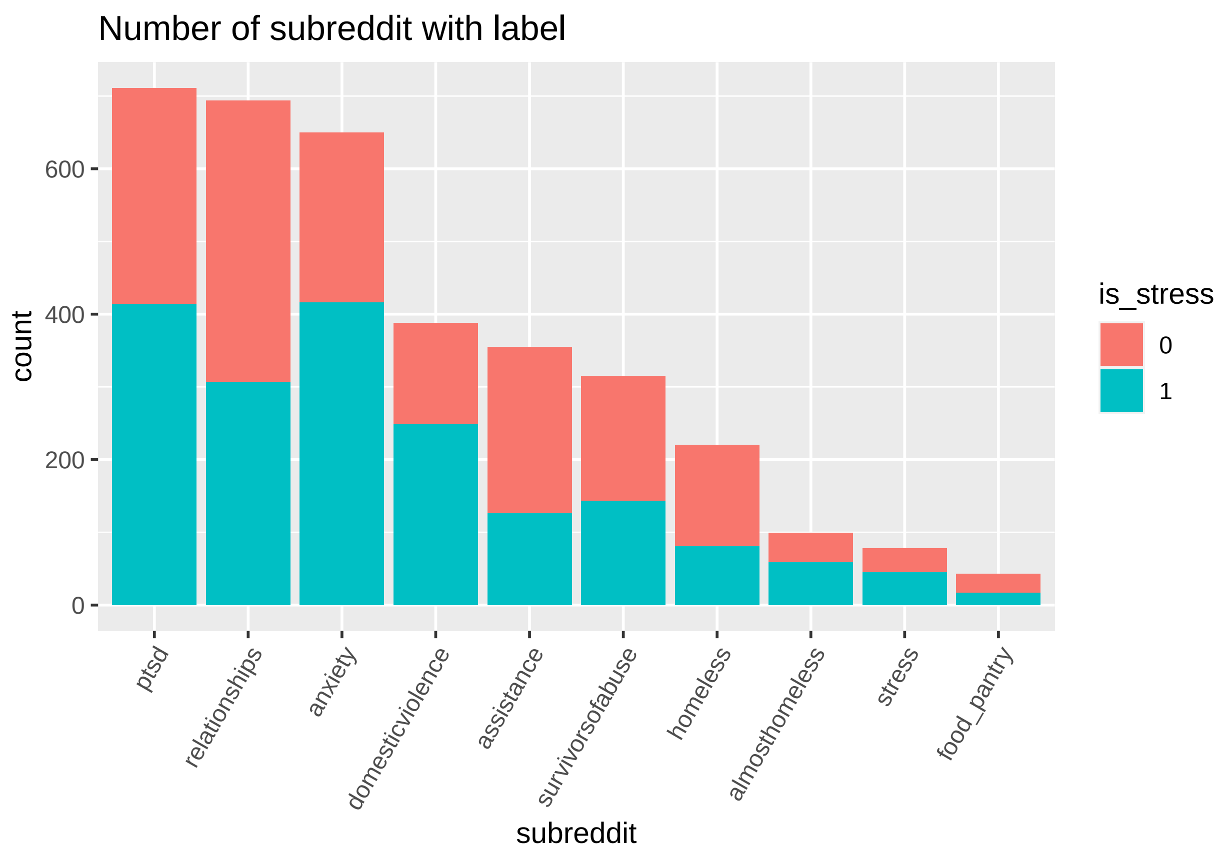
```
##           lex_liwc_power          lex_liwc_reward            lex_liwc_risk
##                        0                        0                        0
##       lex_liwc_focuspast    lex_liwc_focuspresent     lex_liwc_focusfuture
##                        0                        0                        0
##         lex_liwc_relativ          lex_liwc_motion           lex_liwc_space
##                        0                        0                        0
##            lex_liwc_time            lex_liwc_work         lex_liwc_leisure
##                        0                        0                        0
##            lex_liwc_home           lex_liwc_money           lex_liwc_relig
##                        0                        0                        0
##           lex_liwc_death        lex_liwc_informal           lex_liwc_swear
##                        0                        0                        0
##        lex_liwc_netspeak          lex_liwc_assent         lex_liwc_nonflu
##                        0                        0                        0
##          lex_liwc_filler         lex_liwc_AllPunc         lex_liwc_Period
##                        0                        0                        0
##           lex_liwc_Comma           lex_liwc_Colon           lex_liwc_SemiC
##                        0                        0                        0
##           lex_liwc_QMark          lex_liwc_Exclam            lex_liwc_Dash
##                        0                        0                        0
##           lex_liwc_Quote         lex_liwc_Apostro         lex_liwc_Parenth
##                        0                        0                        0
##          lex_liwc_OtherP lex_dal_max_pleasantness   lex_dal_max_activation
##                        0                        0                        0
##      lex_dal_max_imagery lex_dal_min_pleasantness   lex_dal_min_activation
##                        0                        0                        0
##      lex_dal_min_imagery   lex_dal_avg_activation      lex_dal_avg_imagery
##                        0                        0                        0
## lex_dal_avg_pleasantness       social_upvote_ratio      social_num_comments
##                        0                        0                        0
##          syntax_fk_grade                sentiment
##                        0                        0
```

```
## [1] 3553
```

Exploring some of the most important variables

```
df.full <- df.full[, c("subreddit", "text", "label", "social_karma",
                         "social_upvote_ratio", "social_num_comments")] %>%
  rename(is_stress = label)
```

```
result = summarize(group_by(df.full,subreddit, is_stress),
                   count=n())
result$is_stress = factor(result$is_stress)

ggplot(result, aes(fill=is_stress, y=count, x=reorder(subreddit, -count))) +
  geom_bar(position="stack", stat="identity") +
  theme(axis.text.x = element_text(angle = 60, hjust = 1)) +
  ggtitle("Number of subreddit with label") +
  xlab("subreddit")
```




```r
summarize(group_by(df.full,subreddit),
          count=n()) %>% arrange(desc(count))
```

```
## # A tibble: 10 x 2
##    subreddit        count
##    <chr>            <int>
##  1 ptsd               711
##  2 relationships      694
##  3 anxiety            650
##  4 domesticviolence   388
##  5 assistance         355
##  6 survivorsofabuse   315
##  7 homeless           220
##  8 almosthomeless      99
##  9 stress              78
## 10 food_pantry         43
```

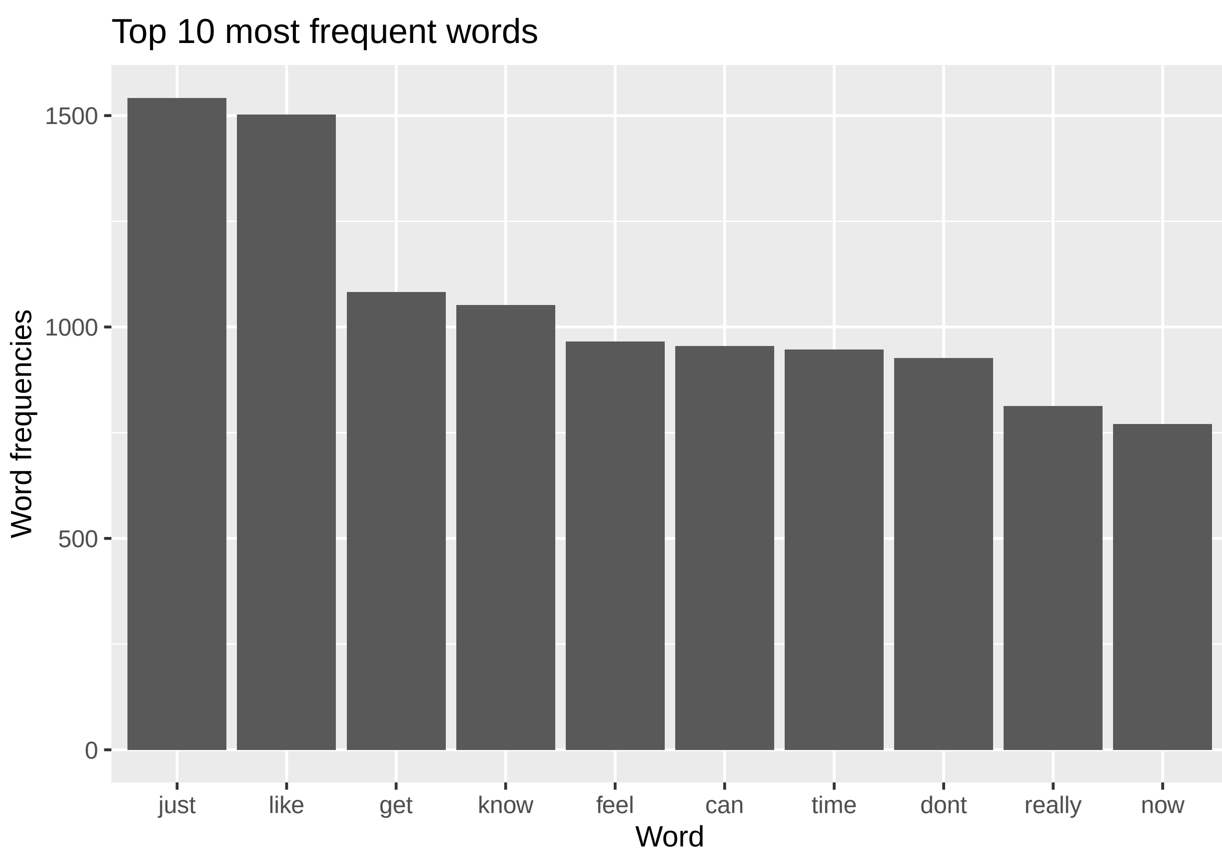
```r
summarize(group_by(df.full,is_stress),
          count=n()) %>% arrange(desc(count))
```

```
## # A tibble: 2 x 2
##   is_stress count
##       <dbl> <int>
## 1         1  1857
## 2         0  1696
```

Sentiment Analysis

```
set.seed(5312)
#Create a vector containing only the text
text <- df.full$text
# Create a corpus
corpus <- Corpus(VectorSource(text))

corpus <- corpus %>%
  tm_map(removeNumbers) %>%
  tm_map(removePunctuation) %>%
  tm_map(stripWhitespace)
corpus <- tm_map(corpus, content_transformer(tolower))
corpus <- tm_map(corpus, removeWords, stopwords("english"))

dtm <- TermDocumentMatrix(corpus)
dtm.M <- as.matrix(dtm)
words <- sort(rowSums(dtm.M),decreasing=TRUE)
dtm_df <- data.frame(word = names(words),freq=words)
```

```
ggplot(dtm_df[1:10,], aes(y=freq, x=reorder(word, -freq))) +
  geom_bar(position="stack", stat="identity") +
  ggtitle("Top 10 most frequent words") +
  ylab("Word frequencies") + xlab("Word")
```



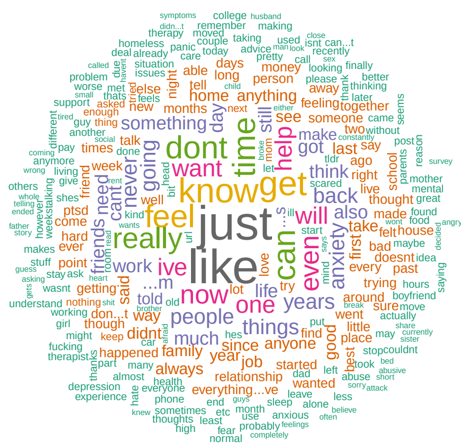
```r
dtm_df[1:10,]
```

```
##          word freq
## just     just 1542
## like     like 1503
## get       get 1083
## know     know 1052
## feel     feel  966
## can       can  955
## time     time  947
## dont     dont  927
## really really  813
## now       now  770
```

```r
gen_dtm_df <- function(df) {
    #Create a vector containing only the text
    text <- df$text
    # Create a corpus
    corpus <- Corpus(VectorSource(text))

    corpus <- corpus %>%
      tm_map(removeNumbers) %>%
      tm_map(removePunctuation) %>%
      tm_map(stripWhitespace)
    corpus <- tm_map(corpus, content_transformer(tolower))
    corpus <- tm_map(corpus, removeWords, stopwords("english"))

    dtm <- TermDocumentMatrix(corpus)
    dtm.M <- as.matrix(dtm)
    words <- sort(rowSums(dtm.M),decreasing=TRUE)
    dtm_df <- data.frame(word = names(words),freq=words)
    top10_bar <- ggplot(dtm_df[1:10,], aes(y=freq, x=reorder(word, -freq))) +
      geom_bar(position="stack", stat="identity") +
      ggtitle("Top 10 most frequent words") +
      ylab("Word frequencies") + xlab("Word")
    return(top10_bar)
}

# gen_dtm_df(df.full)
# gen_dtm_df(df.full[df.full$subreddit == "ptsd", ])
# gen_dtm_df(df.full[df.full$subreddit == "assistance", ])
# gen_dtm_df(df.full[df.full$subreddit == "relationships", ])
# gen_dtm_df(df.full[df.full$subreddit == "survivorsofabuse", ])
# gen_dtm_df(df.full[df.full$subreddit == "domesticviolence", ])
# gen_dtm_df(df.full[df.full$subreddit == "anxiety", ])
# gen_dtm_df(df.full[df.full$subreddit == "homeless", ])
# gen_dtm_df(df.full[df.full$subreddit == "food_pantry", ])
# gen_dtm_df(df.full[df.full$subreddit == "almosthomeless", ])
# gen_dtm_df(df.full[df.full$subreddit == "stress", ])
```

Word Cloud

```r
set.seed(5312)
wordcloud(dtm_df$word,dtm_df$freq, scale=c(1.5,.2),min.freq=3,
          max.words=300, random.order=FALSE, rot.per=.15,
          colors=brewer.pal(8, "Dark2"))
```

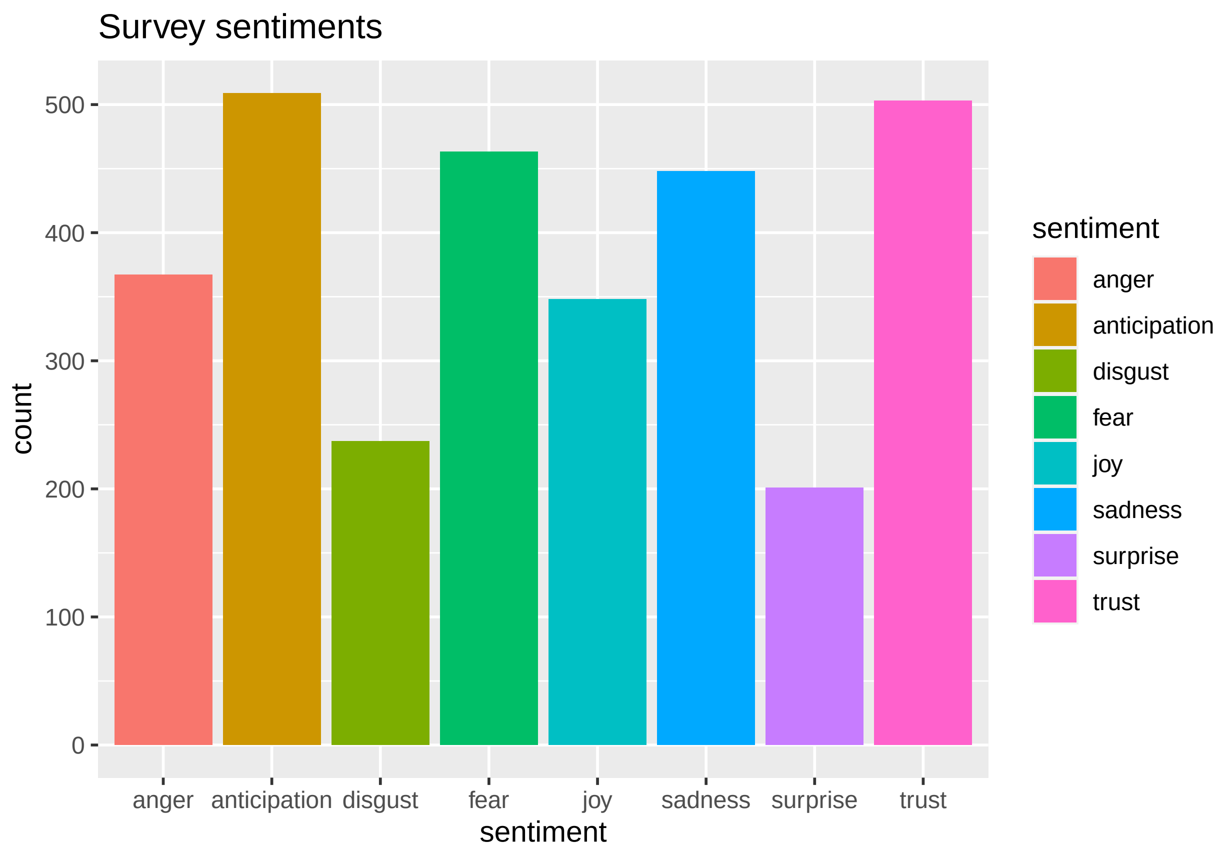



```r
# findAssocs(dtm, terms = findFreqTerms(dtm, lowfreq = 900), corlimit = 0.25)
```

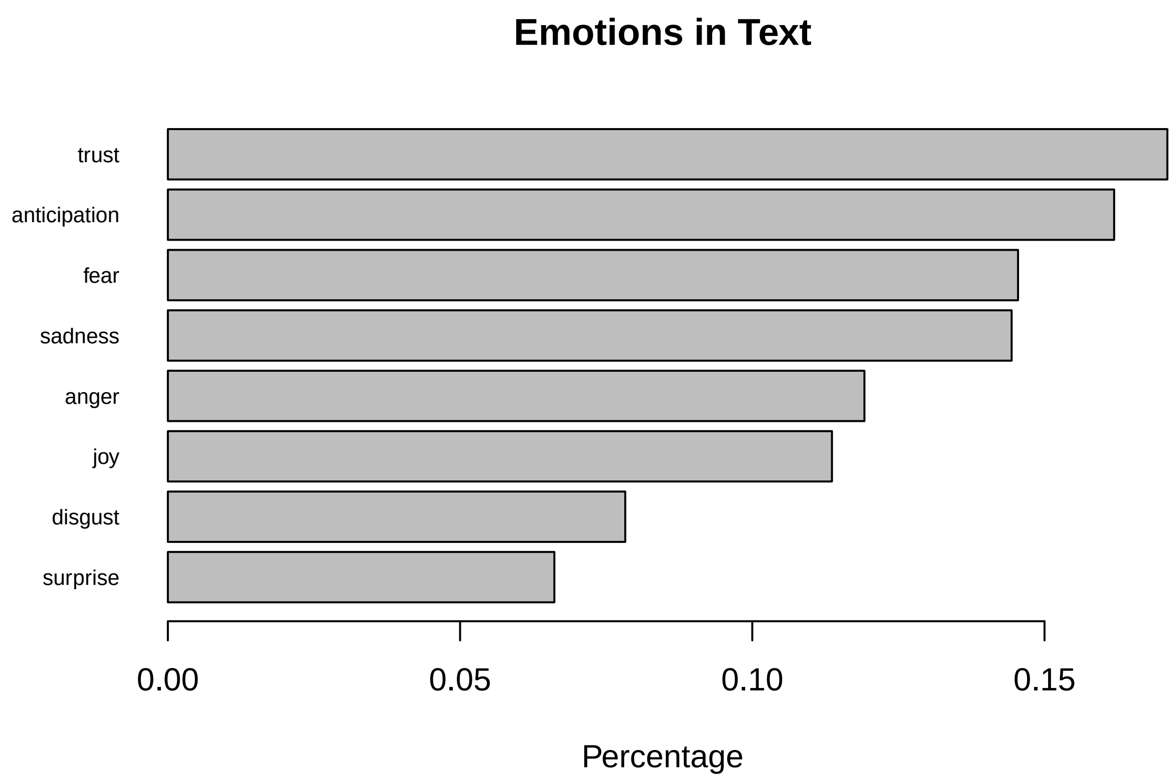
```r
# regular sentiment score using get_sentiment() function and method of your choice
# please note that different methods may have different scales
# -1 - +1
set.seed(5312)
syuzhet <- get_sentiment(df.full$text, method="syuzhet")
df.full$syuzhet <- syuzhet

# bing
bing <- get_sentiment(df.full$text, method="bing")
df.full$bing <- bing

#affin
afinn <- get_sentiment(df.full$text, method="afinn")
df.full$afinn <- afinn
```

```
# run nrc sentiment analysis to return data frame with each row classified as one of the following
# emotions, rather than a score:
# anger, anticipation, disgust, fear, joy, sadness, surprise, trust
# It also counts the number of positive and negative emotions found in each row
nrc<-get_nrc_sentiment(df.full$text)

df.full <- cbind(df.full, nrc)

# standardize
df.full[4:19] <- scale(df.full[4:19])
```

```
#transpose
td<-data.frame(t(nrc))
#The function rowSums computes column sums across rows for each level of a grouping variable.
td_new <- data.frame(rowSums(td[2:253]))
#Transformation and cleaning
names(td_new)[1] <- "count"
td_new <- cbind("sentiment" = rownames(td_new), td_new)
rownames(td_new) <- NULL
td_new2<-td_new[1:8,]
#Plot One - count of words associated with each sentiment
quickplot(sentiment, data=td_new2, weight=count, geom="bar", fill=sentiment, ylab="count")+ggtitle("Sur
```



```r
#Plot two - count of words associated with each sentiment, expressed as a percentage
barplot(
  sort(colSums(prop.table(nrc[, 1:8]))),
  horiz = TRUE,
  cex.names = 0.7,
  las = 1,
  main = "Emotions in Text", xlab="Percentage"
)
```



Prediction

```r
set.seed(5312)
train_size <- floor(0.8 * nrow(df.full))

in_rows <- sample(c(1:nrow(df.full)), size = train_size, replace = FALSE)

df.train <- df.full[in_rows, ]
df.test <- df.full[-in_rows, ]

df.train = df.train[-(1:2)]
df.train$is_stress = as.factor(df.train$is_stress)
df.test$is_stress = as.factor(df.test$is_stress)
```

```r
# Run algorithms using 10-fold cross validation
control <- trainControl(method="cv", number=10)
metric <- "Accuracy"
```

Logistic regression

```r
# df.train.stress = df.train[df.train$is_stress == 1, ]
set.seed(5312)
lr.fit <- glm(formula = is_stress ~ ., data = df.train, family=binomial)
summary(lr.fit)
```

```
##
## Call:
## glm(formula = is_stress ~ ., family = binomial, data = df.train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.2210  -0.9563   0.3323   0.9603   2.4572
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)          0.187569   0.043551   4.307 1.66e-05 ***
## social_karma        -0.290456   0.086242  -3.368 0.000757 ***
## social_upvote_ratio  0.104413   0.043711   2.389 0.016908 *
## social_num_comments  0.121356   0.070339   1.725 0.084475 .
## syuzhet             -0.634028   0.121587  -5.215 1.84e-07 ***
## bing                 0.018100   0.090128   0.201 0.840838
## afinn               -0.453998   0.095298  -4.764 1.90e-06 ***
## anger                0.073398   0.080902   0.907 0.364279
## anticipation        -0.037069   0.057635  -0.643 0.520122
## disgust             -0.067970   0.065484  -1.038 0.299291
## fear                 0.008741   0.076870   0.114 0.909466
## joy                 -0.018343   0.073268  -0.250 0.802315
## sadness              0.152041   0.079155   1.921 0.054757 .
## surprise             0.132108   0.053142   2.486 0.012921 *
## trust               -0.002089   0.064824  -0.032 0.974292
## negative             0.156284   0.100792   1.551 0.121009
## positive             0.064467   0.076763   0.840 0.401011
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 3932.8  on 2841  degrees of freedom
## Residual deviance: 3220.7  on 2825  degrees of freedom
## AIC: 3254.7
##
## Number of Fisher Scoring iterations: 4
```

```r
set.seed(5312)
summary(lr.fit2)
```

```
##
## Call:
## glm(formula = is_stress ~ social_karma + social_upvote_ratio +
##     social_num_comments + syuzhet + afinn + sadness + surprise +
##     negative, family = binomial, data = df.train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.2097  -0.9555   0.3392   0.9605   2.4173
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)          0.18590    0.04346   4.277 1.89e-05 ***
## social_karma        -0.28379    0.08554  -3.318 0.000908 ***
## social_upvote_ratio  0.10601    0.04351   2.437 0.014827 *
## social_num_comments  0.11500    0.06982   1.647 0.099523 .
## syuzhet             -0.59020    0.09027  -6.538 6.22e-11 ***
## afinn               -0.46471    0.08899  -5.222 1.77e-07 ***
## sadness              0.14912    0.07459   1.999 0.045593 *
## surprise             0.12525    0.04744   2.640 0.008284 **
## negative             0.17835    0.08484   2.102 0.035540 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 3932.8  on 2841  degrees of freedom
## Residual deviance: 3223.4  on 2833  degrees of freedom
## AIC: 3241.4
##
## Number of Fisher Scoring iterations: 4
```

```r
# The Variance Inflation Factor(VIF) is used to measure the multicollinearity between predictor variabl

# VIF(lr.fit2)

set.seed(5312)
lr.fit3 <- train(is_stress ~ social_karma + social_upvote_ratio +
                   social_num_comments + syuzhet + afinn +
                   sadness + surprise + negative, data=df.train,
                 method="glm", metric=metric, trControl=control)
summary(lr.fit3)
```

```
##
## Call:
## NULL
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
```

```
## -3.2097  -0.9555   0.3392   0.9605   2.4173
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)          0.18590    0.04346   4.277 1.89e-05 ***
## social_karma        -0.28379    0.08554  -3.318 0.000908 ***
## social_upvote_ratio  0.10601    0.04351   2.437 0.014827 *
## social_num_comments  0.11500    0.06982   1.647 0.099523 .
## syuzhet             -0.59020    0.09027  -6.538 6.22e-11 ***
## afinn               -0.46471    0.08899  -5.222 1.77e-07 ***
## sadness              0.14912    0.07459   1.999 0.045593 *
## surprise             0.12525    0.04744   2.640 0.008284 **
## negative             0.17835    0.08484   2.102 0.035540 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 3932.8  on 2841  degrees of freedom
## Residual deviance: 3223.4  on 2833  degrees of freedom
## AIC: 3241.4
##
## Number of Fisher Scoring iterations: 4
```

Decision tree

```r
set.seed(5312)
dt.fit <- train(is_stress ~ ., data=df.train, method="rpart", metric=metric, trControl=control)
```

Random forest

```r
set.seed(5312)
rf.fit <- train(is_stress ~ ., data=df.train, method="rf", metric=metric, trControl=control)
```

SVM

```r
set.seed(5312)
svm.fit <- train(is_stress ~ ., data=df.train, method="svmRadial", metric=metric, trControl=control)
```

GBM

```r
set.seed(5312)
gbm.fit <- train(is_stress ~ ., data=df.train, method="gbm",
                 metric=metric, trControl=control, verbose=FALSE)
```

Conclusion

```
set.seed(5312)
AccCalc <- function(TestFit, name) {
    # prediction
    predictedval <- predict(TestFit, newdata=df.test)

    # summarize results with confusion matrix
    cm <- confusionMatrix(predictedval, df.test$is_stress)

    # calculate accuracy of the model
    Accuracy<-round(cm$overall[1],4)
    Sensitivity <- round(cm$byClass[1], 4)
    Specificity <- round(cm$byClass[2], 4)
    acc <- data.frame(Accuracy, Sensitivity, Specificity)

    roc_obj <- roc(df.test$is_stress, as.numeric(predictedval))
    acc$Auc <- auc(roc_obj)

    acc$FitName <- name
    return(acc)
}

accAll <- AccCalc(lr.fit3, "lr")
accAll <- rbind(accAll, AccCalc(dt.fit, "dt"))
accAll <- rbind(accAll, AccCalc(rf.fit, "rf"))
accAll <- rbind(accAll, AccCalc(svm.fit, "svm"))
accAll <- rbind(accAll, AccCalc(gbm.fit, "gbm"))
rownames(accAll) <- c()
arrange(accAll,desc(Accuracy))
```

```
##   Accuracy Sensitivity Specificity       Auc FitName
## 1   0.7201      0.6647      0.7726 0.7186713      lr
## 2   0.7117      0.6445      0.7753 0.7099256     gbm
## 3   0.7089      0.6329      0.7808 0.7068849      rf
## 4   0.7032      0.5983      0.8027 0.7005028     svm
## 5   0.6906      0.6387      0.7397 0.6892272      dt
```

```
set.seed(5312)
pred.lr <- predict(lr.fit3, newdata=df.test)
pred.dt <- predict(dt.fit, newdata=df.test)
pred.rf <- predict(rf.fit, newdata=df.test)
pred.svm <- predict(svm.fit, newdata=df.test)
pred.gbm <- predict(gbm.fit, newdata=df.test)

lr.roc <- roc(response = df.test$is_stress, predictor = as.numeric(pred.lr))
dt.roc <- roc(response = df.test$is_stress, predictor = as.numeric(pred.dt))
rf.roc <- roc(response = df.test$is_stress, predictor = as.numeric(pred.rf))
svm.roc <- roc(response = df.test$is_stress, predictor = as.numeric(pred.svm))
gbm.roc <- roc(response = df.test$is_stress, predictor = as.numeric(pred.gbm))

plot(lr.roc, legacy.axes = TRUE, print.auc.y = 0.95, print.auc = TRUE, print.auc.x = 0)
```

```
plot(dt.roc, col = "blue", add = TRUE, print.auc.y = 0.55, print.auc = TRUE, print.auc.x = 0)
plot(rf.roc, col = "red" , add = TRUE, print.auc.y = 0.75, print.auc = TRUE, print.auc.x = 0)
plot(svm.roc, col = "darkgreen" , add = TRUE, print.auc.y = 0.65, print.auc = TRUE, print.auc.x = 0)
plot(gbm.roc, col = "orange" , add = TRUE, print.auc.y = 0.85, print.auc = TRUE, print.auc.x = 0)
legend("bottomright", c("Logistic", "Decision Tree", "Random Forest", "SVM", "GBM"),
       lty = c(1,1), lwd = c(2, 2), col = c("black", "blue", "red", "darkgreen", "orange"), cex = 0.75)
```