Sociophonetics Autocoding

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1) Description of Data

- 2 datasets, for token and their extracted acoustic features
- 2 datasets come from a published paper in sociophonetics
- Dataset 1 of /r/ variable: 40,614 rows and 217 columns
    - 4,255 rows absent of /r/
    - 1,646 rows present of /r/
    - Other rows not yet coded for absent or present
- Dataset 2 of /t/ variable : 9,888 rows and 137 columns

2) Question 1: Autocode the /r/ variable–test different models' behavior on classifying the present versus absent of /r/

a) The data that will be used for this question (specific identification of fields, especially target): dataset 1 only, the target will be the Rpresent column where absent and present is partially hand-coded

b) Description of what you do with the data before modeling

i) Exploratory data analysis and Variable transformations

- Convert categorical variables to numerical ones if necessary
- For numerical variables, standardize them and see whether there is correlation among X variables. Some variables are just one-step next to other variables which have high correlation. In other words, in an acoustic waveform, the 25% timestamp indicate similarly information as the 30% timestamp info. In some models, it makes sense to only include one (e.g., 25%) of the highly correlated variables.

c) Description of Modeling to be done

We will use the following models for this question, and Naive Bayes will be the baseline. It's likely that random forests will perform well for this question.

Model Names	Evaluation Methods	Visualizations
Naive Bayes (Baseline)	Confusion Matrix	Contour Plot
Linear Discriminant Model (LDA)	Confusion Matrix	Contour Plot
Quadratic Discriminant Model (QDA)	Confusion Matrix	Contour Plot
Below models use train-test split and hyperparameter tuning if necessary.		
Logistic Regression (Lasso, Ridge)	Confusion Matrix	Contour Plot
KNN	Confusion Matrix	Contour Plot
Random Forests	Confusion Matrix	Tree
Xgboost with hyperparameter tuning	Confusion Matrix	Tree
SVM with different Kernels	Confusion Matrix	Scatter Plot

4) Analysis of models—confusion matrix will be compared to the baseline model

3) Question 2: Autocode whether the token is /r/ or /t/– test different models' behavior on distinguishing between /r/ and /t/

a) The data that will be used for this question (specific identification of fields, especially target): dataset 1 and dataset 2

b) Description of what you do with the data before modeling

i) Exploratory data analysis and Variable transformations

- The column names in both datasets are turned into small case for comparison
- Two datasets with shared column names (shared feature information) and the target field (/r/ or /t/) are combined. There is 57 shared columns so that the new dataset has 58 columns and 40,614+9,888=50,502 rows
- The new dataset is unbalanced since there are much more /r/ token
- Standardization and correlation among numerical variables also done
- Categorical variables may need to conver to numerical variables

c) Description of Modeling to be done

Model Names	Evaluation Methods	Visualizations
Naive Bayes (Baseline)	Confusion Matrix	Contour Plot
Linear Discriminant Model (LDA)	Confusion Matrix	Contour Plot
Quadratic Discriminant Model (QDA)	Confusion Matrix	Contour Plot
Below models use train-test split and hyperparameter tuning if necessary.		
Logistic Regression (Lasso, Ridge)	Confusion Matrix	Contour Plot
KNN	Confusion Matrix	Contour Plot
Random Forests	Confusion Matrix	Tree
Xgboost with hyperparameter tuning	Confusion Matrix	Tree
SVM with different Kernels	Confusion Matrix	Scatter Plot

4) Analysis of models—confusion matrix will be compared to the baseline model

EDA

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```
# library install
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.2 --
## v ggplot2 3.3.6     v purrr   0.3.4
## v tibble  3.1.7     v dplyr   1.0.9
## v tidyr   1.2.0     v stringr 1.4.0
## v readr   2.1.2     v forcats 0.5.1
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(sqldf)
```

```
## Loading required package: gsubfn
## Loading required package: proto
## Loading required package: RSQLite
```

```
library(ggplot2)
library(ggcorrplot)
```

Our project focus on two questions: 1. for the word with ˚ train the model to fine whether the speaker misses this pronounciation 2. according to the pronounciation, determine whether this words has ˚ or ˆ

```
Rclass <- readRDS("/Users/apple/Desktop/STT811_appl_stat_model/pro/data/RClassifierData_03July2019.Rds")
Tclass <- readRDS("/Users/apple/Desktop/STT811_appl_stat_model/pro/data/TClassifierData_14Nov2019.Rds")
```

see the size of 2 dataframe

```
dim(Rclass)
```

```
## [1] 40614   217
```

```
dim(Tclass)
```

```
## [1] 9888  137
```

1. EDA for question 1

```
dim(Rclass)
```

```
## [1] 40614   217
```

```
sqldf("SELECT DISTINCT Rpresent
       FROM Rclass")
```

```
##   Rpresent
## 1     <NA>
## 2   Absent
## 3  Present
```

```
sqldf("SELECT COUNT(*)
      FROM Rclass
      WHERE Rpresent = 'Absent' ")
```

```
##   COUNT(*)
## 1     4255
```

see the number of data have been coded 'present'(means pronoucing the ˚) and 'absent' (means missing the ˚)

```
sqldf("SELECT COUNT(*)
      FROM Rclass
      WHERE Rpresent = 'Present' ")
```

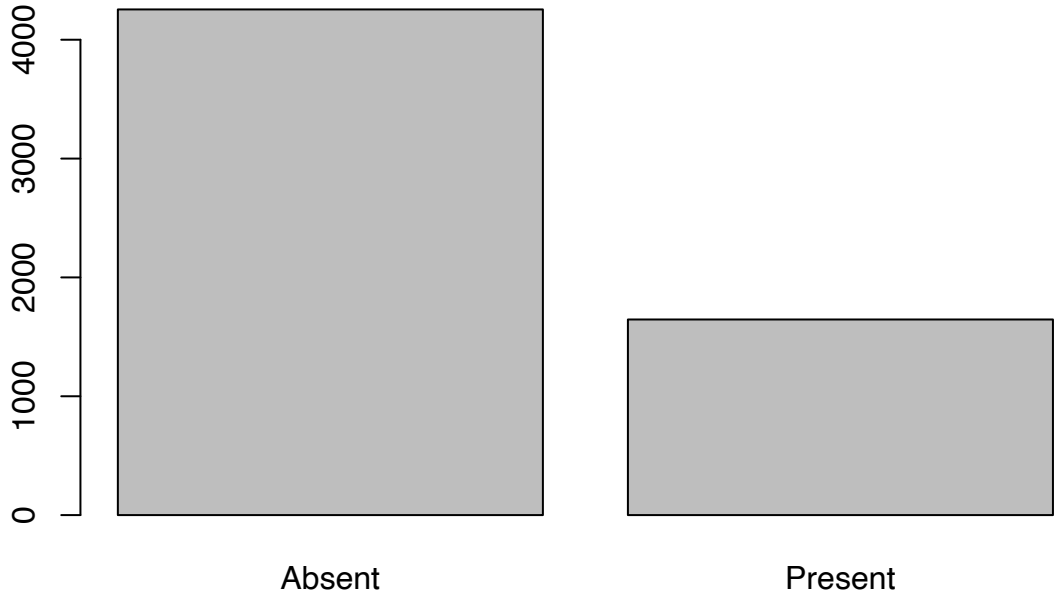
```
##   COUNT(*)
## 1     1646
```

```
sqldf("SELECT COUNT(*)
      FROM Rclass
      WHERE Rpresent = 'Absent' ")
```

```
##   COUNT(*)
## 1     4255
```

```
rdf_pre_ab <- sqldf("SELECT *
                    FROM Rclass
                    WHERE Rpresent = 'Absent' OR Rpresent = 'Present'")
```

```
barplot(table(rdf_pre_ab$Rpresent))
```



we can see that the data are unbalanced.

extract the columns I think useful

```
rdf_useful <- rdf_pre_ab[34:217]
rdf_useful$Rpresent <- rdf_pre_ab$Rpresent
rdf_useful <- na.omit(rdf_useful)
dim(rdf_useful)
```

```
## [1] 5273  185
```

encode absent - 0; present - 1

```
rdf_useful$Rpresent_encode <- ifelse(rdf_useful$Rpresent == "Present", 1, 0)
```

standardize the data

```
# Standardize the data
standardized_rdata <- scale(rdf_useful[, c(1:184)], center = TRUE, scale = TRUE)
rdf_useful[, c(1:184)] <- standardized_rdata
```

the correlation between elements

```
cor_rdf_usefurl <- round(cor(rdf_useful[, c(1:184, 186)]), 2)
write_csv(as.data.frame(cor_rdf_usefurl), file = "rdf_correlation.csv")
```

print all the variables name, whose correlations are higher than 0.9

```
high_corr <- data.frame(var1 = character() , var2 = character(), cor = numeric())
z = 1
for (i in 1:185) {
  for (j in 1:i) {
    if (abs(cor_rdf_usefurl[i, j]) > 0.9 && i != j) {
      high_corr[z, 1] <- colnames(cor_rdf_usefurl)[j]
      high_corr[z, 2] <- colnames(cor_rdf_usefurl)[i]
      high_corr[z, 3] <- cor_rdf_usefurl[i, j]
      z = z +1
    }
  }
}
high_corr
```

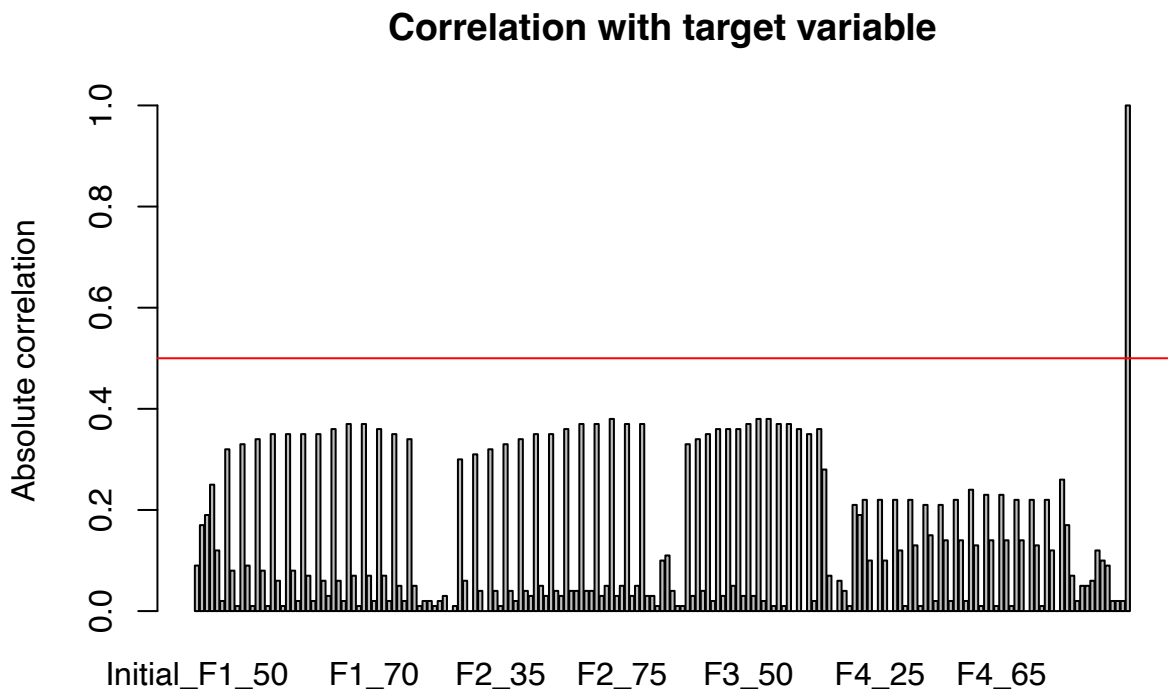
```
##            var1         var2  cor
## 1         F1_20        F1_25 0.92
## 2   diffF3F1_20  diffF3F1_25 0.93
## 3         F1_25        F1_30 0.93
## 4   diffF3F1_25  diffF3F1_30 0.94
## 5   diffF3F1_30  diffF3F1_35 0.94
## 6         F1_35        F1_40 0.93
## 7   diffF3F1_35  diffF3F1_40 0.94
## 8         F1_40        F1_45 0.95
## 9   diffF3F1_40  diffF3F1_45 0.94
## 10        F1_45        F1_50 0.93
## 11  diffF3F1_45  diffF3F1_50 0.92
## 12        F1_50        F1_55 0.93
## 13  diffF3F1_50  diffF3F1_55 0.92
## 14        F1_55        F1_60 0.92
## 15  diffF3F1_55  diffF3F1_60 0.93
## 16        F1_60        F1_65 0.92
## 17  diffF3F1_60  diffF3F1_65 0.93
## 18  diffF3F1_65  diffF3F1_70 0.93
## 19  diffF3F1_70  diffF3F1_75 0.92
## 20        F1_75        F1_80 0.91
## 21  diffF3F1_75  diffF3F1_80 0.92
## 22        F2_20        F2_25 0.92
## 23  diffF3F2_20  diffF3F2_25 0.94
## 24        F2_25        F2_30 0.94
## 25  diffF3F2_25  diffF3F2_30 0.95
## 26        F2_30        F2_35 0.93
## 27  diffF3F2_30  diffF3F2_35 0.95
## 28        F2_35        F2_40 0.94
## 29  diffF3F2_30  diffF3F2_40 0.91
## 30  diffF3F2_35  diffF3F2_40 0.96
## 31        F2_40        F2_45 0.94
## 32  diffF3F2_40  diffF3F2_45 0.95
## 33        F2_45        F2_50 0.94
## 34  diffF3F2_45  diffF3F2_50 0.94
## 35        F2_50        F2_55 0.93
## 36  diffF3F2_45  diffF3F2_55 0.91
## 37  diffF3F2_50  diffF3F2_55 0.94
```

```
## 38        F2_55        F2_60 0.94
## 39  diffF3F2_55  diffF3F2_60 0.95
## 40        F2_60        F2_65 0.93
## 41  diffF3F2_60  diffF3F2_65 0.95
## 42        F2_65        F2_70 0.94
## 43  diffF3F2_65  diffF3F2_70 0.95
## 44        F2_70        F2_75 0.92
## 45  diffF3F2_70  diffF3F2_75 0.94
## 46        F2_75        F2_80 0.93
## 47  diffF3F2_75  diffF3F2_80 0.93
## 48  diffF3F1_20        F3_20 0.94
## 49  diffF3F1_25        F3_25 0.94
## 50        F3_20        F3_25 0.92
## 51  diffF3F1_30        F3_30 0.94
## 52        F3_25        F3_30 0.93
## 53  diffF3F1_35        F3_35 0.94
## 54        F3_30        F3_35 0.93
## 55  diffF3F1_40        F3_40 0.94
## 56        F3_35        F3_40 0.93
## 57  diffF3F1_45        F3_45 0.94
## 58        F3_40        F3_45 0.93
## 59  diffF3F1_50        F3_50 0.94
## 60        F3_45        F3_50 0.91
## 61  diffF3F1_55        F3_55 0.94
## 62        F3_50        F3_55 0.92
## 63  diffF3F1_60        F3_60 0.94
## 64        F3_55        F3_60 0.92
## 65  diffF3F1_65        F3_65 0.94
## 66        F3_60        F3_65 0.91
## 67  diffF3F1_70        F3_70 0.93
## 68        F3_65        F3_70 0.93
## 69  diffF3F1_75        F3_75 0.93
## 70        F3_70        F3_75 0.91
## 71  diffF3F1_80        F3_80 0.92
## 72        F3_75        F3_80 0.91
## 73 intens_F3min intens_F3max 0.92
## 74        F4_35        F4_40 0.91
## 75        F4_40        F4_45 0.91
## 76        F0min        F0max 0.96
```

For the variable listed in this dataframe, we are gonna choose var1 and drop var2, when we feed data into classifer.

for the correlation between variables and target

```
barplot(abs(cor_rdf_usefurl[, 185]), main = "Correlation with target variable", ylab = "Absolute correla
abline(h = 0.5, col = "red")
```



we can see the correlation is not really high.

for the variable having highest correlation with target, we will observe the distribution of it.

```
cor_rdf_usefurl_df <- as.data.frame(cor_rdf_usefurl)
head(cor_rdf_usefurl_df)
```

```
##               Initial_F1_50 Initial_F2_50 Initial_F3_50 Initial_F4_50 TokenDur
## Initial_F1_50          1.00          0.30          0.25          0.47     0.02
## Initial_F2_50          0.30          1.00          0.82          0.67     0.06
## Initial_F3_50          0.25          0.82          1.00          0.74     0.04
## Initial_F4_50          0.47          0.67          0.74          1.00    -0.01
## TokenDur               0.02          0.06          0.04         -0.01     1.00
## F1_20                  0.29          0.14          0.12          0.20     0.17
##               F1_20 diffF3F1_20 BW1_20 F1_25 diffF3F1_25 BW1_25 F1_30
## Initial_F1_50  0.29        0.03   0.00  0.30        0.03  -0.01  0.30
## Initial_F2_50  0.14        0.22   0.09  0.14        0.22   0.07  0.13
## Initial_F3_50  0.12        0.33   0.09  0.12        0.32   0.08  0.12
## Initial_F4_50  0.20        0.23   0.10  0.20        0.23   0.08  0.20
## TokenDur       0.17       -0.07   0.02  0.16       -0.06   0.04  0.18
## F1_20          1.00       -0.22   0.13  0.92       -0.22   0.16  0.85
##               diffF3F1_30 BW1_30 F1_35 diffF3F1_35 BW1_35 F1_40 diffF3F1_40
## Initial_F1_50        0.04   0.00  0.31        0.05   0.00  0.32        0.05
## Initial_F2_50        0.23   0.07  0.13        0.24   0.05  0.13        0.25
## Initial_F3_50        0.33   0.08  0.11        0.33   0.07  0.11        0.34
## Initial_F4_50        0.23   0.09  0.20        0.24   0.08  0.20        0.24
```

```
## TokenDur            -0.07   0.03  0.22       -0.08   0.04  0.22       -0.09
## F1_20               -0.21   0.16  0.78       -0.19   0.19  0.73       -0.18
##               BW1_40 F1_45 diffF3F1_45 BW1_45 F1_50 diffF3F1_50 BW1_50 F1_55
## Initial_F1_50   0.01  0.31        0.06  -0.01  0.29        0.06   0.00  0.29
## Initial_F2_50   0.06  0.12        0.25   0.04  0.12        0.25   0.04  0.13
## Initial_F3_50   0.07  0.11        0.33   0.05  0.10        0.33   0.04  0.11
## Initial_F4_50   0.08  0.19        0.24   0.05  0.19        0.25   0.05  0.19
## TokenDur        0.05  0.23       -0.10   0.05  0.19       -0.11   0.06  0.22
## F1_20           0.16  0.71       -0.18   0.15  0.69       -0.17   0.13  0.68
##               diffF3F1_55 BW1_55 F1_60 diffF3F1_60 BW1_60 F1_65 diffF3F1_65
## Initial_F1_50        0.07   0.00  0.29        0.08   0.01  0.28        0.10
## Initial_F2_50        0.26   0.05  0.12        0.27   0.06  0.11        0.28
## Initial_F3_50        0.34   0.05  0.11        0.35   0.07  0.10        0.36
## Initial_F4_50        0.27   0.05  0.18        0.29   0.06  0.17        0.30
## TokenDur            -0.11   0.05  0.22       -0.11   0.12  0.21       -0.12
## F1_20               -0.16   0.13  0.64       -0.17   0.14  0.60       -0.15
##               BW1_65 F1_70 diffF3F1_70 BW1_70 F1_75 diffF3F1_75 BW1_75 F1_80
## Initial_F1_50   0.00  0.27        0.10   0.01  0.25        0.11   0.02  0.24
## Initial_F2_50   0.06  0.09        0.29   0.07  0.07        0.29   0.07  0.06
## Initial_F3_50   0.08  0.09        0.37   0.08  0.07        0.37   0.08  0.06
## Initial_F4_50   0.07  0.15        0.31   0.06  0.13        0.33   0.06  0.11
## TokenDur        0.06  0.22       -0.12   0.13  0.20       -0.12   0.08  0.20
## F1_20           0.14  0.57       -0.14   0.15  0.53       -0.13   0.15  0.50
##               diffF3F1_80 BW1_80 F1min F1max time_F1min time_F1max F1range
## Initial_F1_50        0.13   0.00  0.29  0.16       0.01      -0.01   -0.01
## Initial_F2_50        0.31   0.05  0.03  0.11       0.00      -0.02    0.08
## Initial_F3_50        0.39   0.07  0.01  0.11      -0.02       0.00    0.10
## Initial_F4_50        0.35   0.05  0.10  0.12       0.01      -0.03    0.06
## TokenDur            -0.12   0.09 -0.05  0.37      -0.04       0.13    0.37
## F1_20               -0.11   0.13  0.53  0.63       0.12      -0.17    0.29
##               time_F1range slopeF1 F2_20 diffF3F2_20 BW2_20 F2_25 diffF3F2_25
## Initial_F1_50         0.01   -0.02  0.02        0.11   0.09  0.02        0.11
## Initial_F2_50        -0.02    0.01  0.14        0.12   0.09  0.14        0.12
## Initial_F3_50        -0.04    0.03  0.09        0.26   0.13  0.09        0.25
## Initial_F4_50        -0.02    0.00  0.05        0.23   0.21  0.05        0.23
## TokenDur             -0.28    0.41  0.01       -0.02  -0.02  0.01       -0.02
## F1_20                -0.07    0.11  0.18       -0.04   0.02  0.14       -0.04
##               BW2_25 F2_30 diffF3F2_30 BW2_30 F2_35 diffF3F2_35 BW2_35 F2_40
## Initial_F1_50   0.08  0.02        0.11   0.09  0.03        0.11   0.08  0.03
## Initial_F2_50   0.10  0.15        0.11   0.11  0.15        0.13   0.11  0.15
## Initial_F3_50   0.15  0.09        0.25   0.15  0.08        0.26   0.15  0.09
## Initial_F4_50   0.21  0.05        0.22   0.21  0.05        0.23   0.21  0.05
## TokenDur       -0.04  0.01       -0.02  -0.04  0.02       -0.02  -0.02  0.01
## F1_20           0.02  0.12       -0.03   0.01  0.09       -0.02   0.00  0.08
##               diffF3F2_40 BW2_40 F2_45 diffF3F2_45 BW2_45 F2_50 diffF3F2_50
## Initial_F1_50        0.12   0.09  0.03        0.11   0.10  0.04        0.11
## Initial_F2_50        0.13   0.09  0.15        0.13   0.10  0.14        0.13
## Initial_F3_50        0.26   0.14  0.09        0.25   0.14  0.08        0.26
## Initial_F4_50        0.24   0.20  0.06        0.23   0.20  0.06        0.24
## TokenDur            -0.03  -0.04  0.02       -0.04  -0.04  0.00       -0.04
## F1_20               -0.02  -0.01  0.08       -0.02  -0.01  0.08       -0.01
##               BW2_50 F2_55 diffF3F2_55 BW2_55 F2_60 diffF3F2_60 BW2_60 F2_65
## Initial_F1_50   0.09  0.05        0.12   0.11  0.05        0.12   0.10  0.06
## Initial_F2_50   0.10  0.16        0.13   0.10  0.16        0.14   0.10  0.17
```

```
## Initial_F3_50   0.15  0.09        0.27   0.15  0.09        0.27   0.14  0.10
## Initial_F4_50   0.20  0.06        0.25   0.20  0.07        0.25   0.19  0.08
## TokenDur       -0.04  0.01       -0.04  -0.03  0.01       -0.04  -0.05  0.02
## F1_20          -0.01  0.09       -0.01  -0.01  0.09       -0.02  -0.02  0.08
##               diffF3F2_65 BW2_65 F2_70 diffF3F2_70 BW2_70 F2_75 diffF3F2_75
## Initial_F1_50        0.13   0.10  0.06        0.13   0.10  0.06        0.14
## Initial_F2_50        0.15   0.10  0.16        0.15   0.10  0.16        0.16
## Initial_F3_50        0.28   0.15  0.10        0.28   0.15  0.10        0.29
## Initial_F4_50        0.26   0.21  0.08        0.26   0.21  0.09        0.27
## TokenDur            -0.06  -0.05  0.01       -0.05  -0.07  0.00       -0.05
## F1_20               -0.01   0.00  0.08       -0.01   0.01  0.07        0.01
##               BW2_75 F2_80 diffF3F2_80 BW2_80 F2min F2max time_F2min time_F2max
## Initial_F1_50   0.08  0.06        0.15   0.08 -0.07  0.10       0.02       0.00
## Initial_F2_50   0.09  0.17        0.17   0.09  0.05  0.21       0.02       0.00
## Initial_F3_50   0.14  0.11        0.30   0.14 -0.03  0.19       0.01       0.00
## Initial_F4_50   0.19  0.10        0.29   0.19 -0.11  0.19       0.01      -0.01
## TokenDur       -0.05  0.01       -0.04  -0.03 -0.17  0.21       0.00       0.00
## F1_20           0.00  0.07        0.02   0.01  0.03  0.16       0.03      -0.04
##               F2range time_F2range slopeF2 F3_20 BW3_20 F3_25 BW3_25 F3_30
## Initial_F1_50    0.15        -0.06    0.09  0.14   0.14  0.14   0.13  0.14
## Initial_F2_50    0.15        -0.08    0.08  0.28   0.08  0.27   0.09  0.28
## Initial_F3_50    0.19        -0.08    0.10  0.37   0.12  0.37   0.12  0.37
## Initial_F4_50    0.26        -0.10    0.13  0.31   0.16  0.30   0.14  0.30
## TokenDur         0.33        -0.20    0.38 -0.01  -0.02 -0.01  -0.02 -0.01
## F1_20            0.11        -0.08    0.08  0.14   0.04  0.10   0.03  0.08
##               BW3_30 F3_35 BW3_35 F3_40 BW3_40 F3_45 BW3_45 F3_50 BW3_50 F3_55
## Initial_F1_50   0.13  0.15   0.12  0.16   0.13  0.16   0.13  0.16   0.13  0.17
## Initial_F2_50   0.09  0.28   0.08  0.30   0.10  0.29   0.08  0.29   0.08  0.30
## Initial_F3_50   0.11  0.38   0.11  0.38   0.13  0.37   0.12  0.37   0.11  0.38
## Initial_F4_50   0.15  0.31   0.14  0.32   0.16  0.31   0.15  0.32   0.14  0.34
## TokenDur       -0.01 -0.01  -0.02 -0.02  -0.01 -0.02   0.00 -0.05   0.00 -0.03
## F1_20           0.02  0.07   0.01  0.06   0.03  0.06   0.03  0.07   0.02  0.07
##               BW3_55 F3_60 BW3_60 F3_65 BW3_65 F3_70 BW3_70 F3_75 BW3_75 F3_80
## Initial_F1_50   0.15  0.18   0.16  0.20   0.15  0.20   0.15  0.21   0.15  0.22
## Initial_F2_50   0.10  0.31   0.10  0.32   0.10  0.32   0.09  0.32   0.09  0.34
## Initial_F3_50   0.11  0.39   0.12  0.40   0.12  0.41   0.12  0.40   0.13  0.41
## Initial_F4_50   0.15  0.35   0.16  0.36   0.16  0.37   0.17  0.38   0.19  0.40
## TokenDur       -0.01 -0.04   0.00 -0.04   0.03 -0.04   0.02 -0.05   0.01 -0.04
## F1_20           0.03  0.06   0.04  0.06   0.03  0.07   0.03  0.07   0.02  0.08
##               BW3_80 F3min F3max time_F3min time_F3max F3range time_F3range
## Initial_F1_50   0.16  0.05  0.25      -0.03       0.05    0.18        -0.08
## Initial_F2_50   0.09  0.18  0.35      -0.02       0.04    0.16        -0.08
## Initial_F3_50   0.13  0.25  0.45      -0.03       0.03    0.19        -0.08
## Initial_F4_50   0.18  0.19  0.43      -0.05       0.06    0.23        -0.08
## TokenDur        0.02 -0.24  0.19       0.06      -0.02    0.38        -0.23
## F1_20           0.05 -0.01  0.17       0.03      -0.03    0.16        -0.08
##               slopeF3 intens_F3min intens_F3max F4_20 diffF4F3_20 BW4_20 F4_25
## Initial_F1_50    0.11        -0.10        -0.12  0.17        0.05   0.14  0.17
## Initial_F2_50    0.09        -0.10        -0.13  0.30        0.06   0.10  0.30
## Initial_F3_50    0.10        -0.14        -0.16  0.35        0.01   0.05  0.35
## Initial_F4_50    0.11        -0.15        -0.18  0.48        0.23   0.13  0.48
## TokenDur         0.44         0.02        -0.03 -0.06       -0.06  -0.01 -0.05
## F1_20            0.12         0.02        -0.02  0.22        0.11   0.03  0.18
##               diffF4F3_25 BW4_25 F4_30 diffF4F3_30 BW4_30 F4_35 diffF4F3_35
```

```
## Initial_F1_50        0.06   0.15  0.18        0.05   0.15  0.18        0.05
## Initial_F2_50        0.06   0.10  0.30        0.05   0.10  0.30        0.04
## Initial_F3_50        0.01   0.06  0.34        0.01   0.06  0.34        0.00
## Initial_F4_50        0.24   0.14  0.47        0.23   0.14  0.47        0.22
## TokenDur            -0.06  -0.01 -0.06       -0.05   0.00 -0.04       -0.04
## F1_20                0.10   0.04  0.15        0.09   0.04  0.13        0.08
##                BW4_35 F4_40 diffF4F3_40 BW4_40 F4_45 diffF4F3_45 BW4_45 F4_50
## Initial_F1_50    0.15  0.18        0.04   0.15  0.18        0.04   0.15  0.18
## Initial_F2_50    0.11  0.30        0.03   0.11  0.30        0.04   0.12  0.29
## Initial_F3_50    0.06  0.34       -0.01   0.06  0.33       -0.01   0.05  0.32
## Initial_F4_50    0.14  0.48        0.22   0.15  0.47        0.22   0.13  0.46
## TokenDur         0.00 -0.05       -0.04  -0.01 -0.06       -0.04   0.00 -0.07
## F1_20            0.05  0.12        0.09   0.05  0.13        0.09   0.06  0.12
##                diffF4F3_50 BW4_50 F4_55 diffF4F3_55 BW4_55 F4_60 diffF4F3_60
## Initial_F1_50        0.03   0.14  0.19        0.04   0.14  0.20        0.03
## Initial_F2_50        0.03   0.11  0.30        0.03   0.12  0.32        0.04
## Initial_F3_50       -0.02   0.05  0.33       -0.02   0.05  0.35       -0.01
## Initial_F4_50        0.20   0.13  0.48        0.20   0.14  0.49        0.21
## TokenDur            -0.03   0.00 -0.06       -0.03   0.00 -0.04       -0.01
## F1_20                0.07   0.06  0.12        0.07   0.06  0.11        0.07
##                BW4_60 F4_65 diffF4F3_65 BW4_65 F4_70 diffF4F3_70 BW4_70 F4_75
## Initial_F1_50    0.16  0.20        0.03   0.17  0.22        0.04   0.15  0.22
## Initial_F2_50    0.13  0.32        0.03   0.12  0.31        0.03   0.11  0.31
## Initial_F3_50    0.07  0.35       -0.02   0.05  0.35       -0.03   0.04  0.34
## Initial_F4_50    0.16  0.49        0.20   0.15  0.49        0.19   0.14  0.49
## TokenDur         0.03 -0.05       -0.01   0.02 -0.04       -0.01   0.02 -0.06
## F1_20            0.07  0.12        0.07   0.07  0.12        0.08   0.05  0.12
##                diffF4F3_75 BW4_75 F4_80 diffF4F3_80 BW4_80 F4min F4max
## Initial_F1_50        0.04   0.14  0.23        0.03   0.16  0.09  0.27
## Initial_F2_50        0.03   0.11  0.32        0.02   0.13  0.22  0.36
## Initial_F3_50       -0.03   0.05  0.35       -0.03   0.06  0.28  0.37
## Initial_F4_50        0.18   0.13  0.50        0.17   0.15  0.37  0.54
## TokenDur            -0.02   0.04 -0.04        0.00   0.03 -0.28  0.16
## F1_20                0.07   0.04  0.12        0.06   0.04  0.04  0.22
##                time_F4min time_F4max F4range time_F4range slopeF4 F0min F0max
## Initial_F1_50       -0.03       0.01    0.16        -0.06    0.09  0.34  0.34
## Initial_F2_50       -0.03       0.01    0.15        -0.06    0.09  0.45  0.46
## Initial_F3_50       -0.02       0.00    0.10        -0.06    0.06  0.43  0.44
## Initial_F4_50       -0.03       0.00    0.18        -0.08    0.09  0.61  0.60
## TokenDur             0.02       0.01    0.37        -0.26    0.41 -0.07  0.07
## F1_20                0.04      -0.06    0.16        -0.08    0.10  0.17  0.19
##                F0rangeST time_F0min time_F0max absSlopeF0 Rpresent_encode
## Initial_F1_50       0.06      -0.08       0.04       0.17           -0.09
## Initial_F2_50       0.14       0.01      -0.06       0.23           -0.17
## Initial_F3_50       0.11       0.01      -0.03       0.25           -0.19
## Initial_F4_50       0.06       0.00       0.00       0.17           -0.25
## TokenDur            0.54      -0.17       0.08      -0.05            0.12
## F1_20               0.08      -0.05       0.04       0.03           -0.02
```

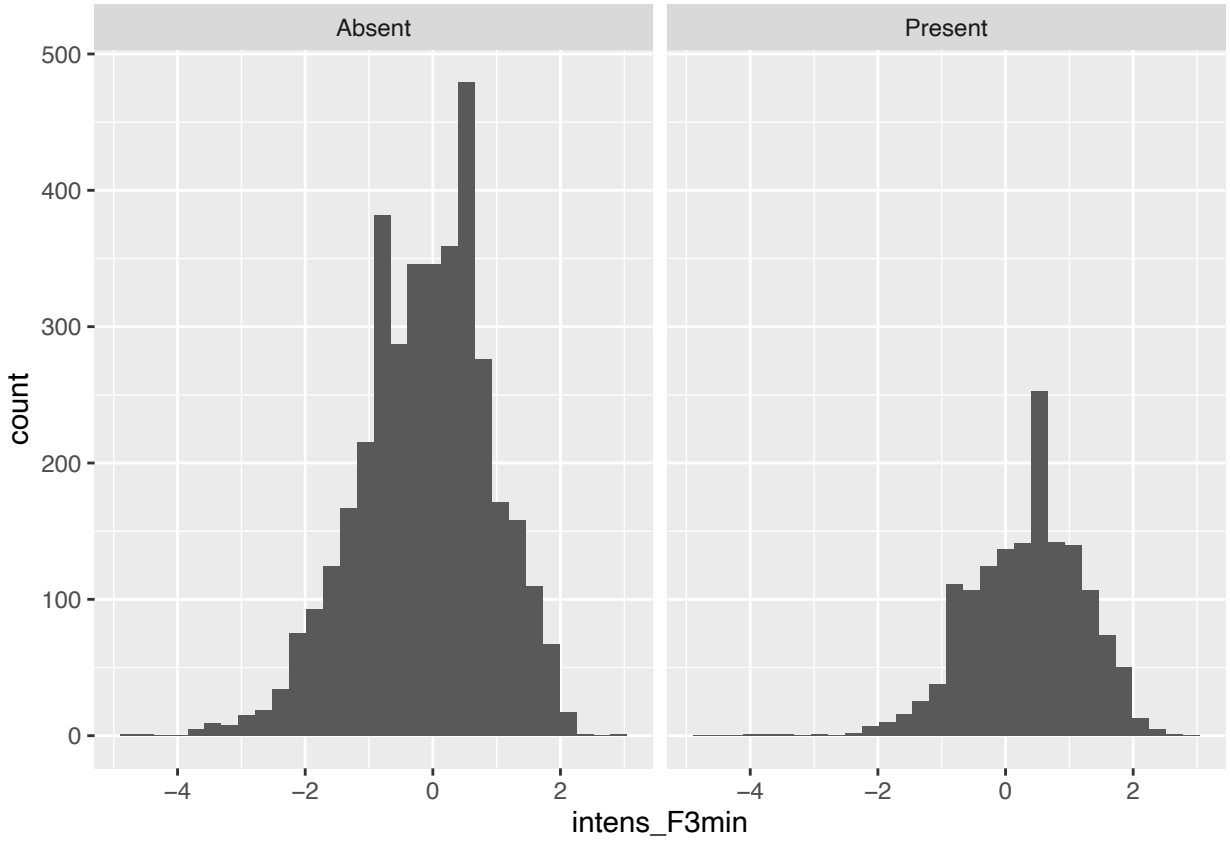
```
cor_rdf_usefurl_df$row <- colnames(cor_rdf_usefurl_df)
df <- sqldf("SELECT row, Rpresent_encode
             FROM cor_rdf_usefurl_df
             ORDER BY Rpresent_encode DESC
             LIMIT 4")
```

```
df
```

```
##               row Rpresent_encode
## 1 Rpresent_encode            1.00
## 2    intens_F3min            0.21
## 3    intens_F3max            0.19
## 4     diffF4F3_40            0.15
```

```
ggplot(data = rdf_useful, aes(x = intens_F3min)) + geom_histogram() + facet_grid(.~Rpresent)
```

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



2. EDA for question 2

```
Rclass_token <- Rclass
Rclass_token$token <- 'r'
```

set column names to the lower case

```
colnames(Rclass_token) <- tolower(colnames(Rclass_token))
colnames(Tclass) <- tolower(colnames(Tclass))
```

list the all same column in two files

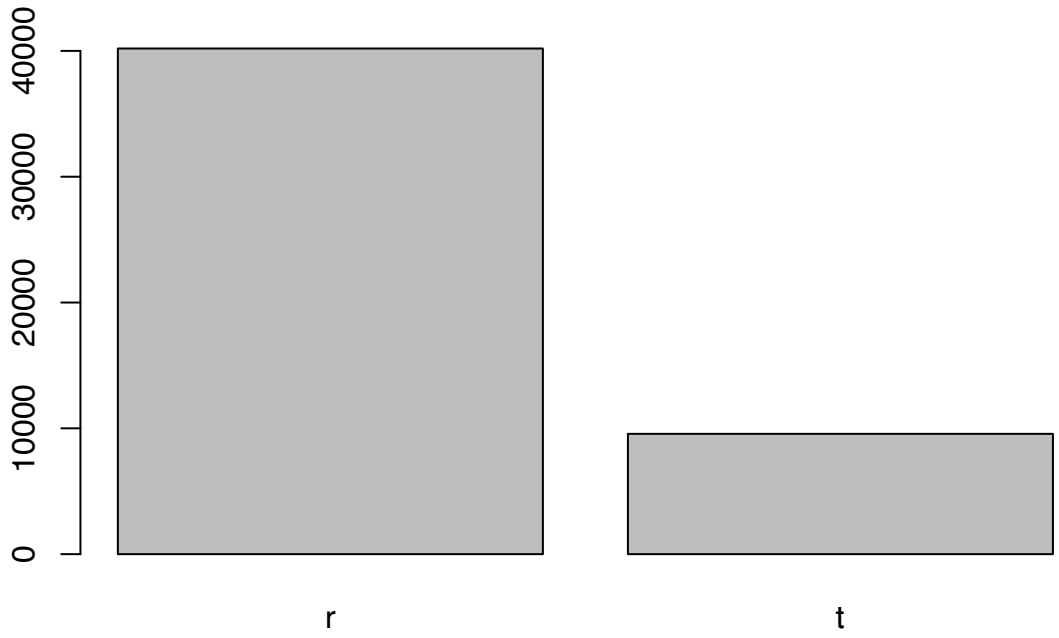
```
same <- Reduce(intersect, list(colnames(Rclass_token), colnames(Tclass)))
same
```

```
##  [1] "tokennum"   "speaker"    "gender"     "matchid"    "stress"
##  [6] "celexfreq"  "syllable"   "syllstart"  "syllend"    "word"
## [11] "wordstart"  "wordend"    "tokenstart" "tokenend"   "corpusfreq"
## [16] "howcoded"   "tokendur"   "bw1_20"     "bw1_25"     "bw1_30"
## [21] "bw1_35"     "bw1_40"     "bw1_45"     "bw1_50"     "bw1_55"
## [26] "bw1_60"     "bw1_65"     "bw1_70"     "bw1_75"     "bw1_80"
## [31] "bw2_20"     "bw2_25"     "bw2_30"     "bw2_35"     "bw2_40"
## [36] "bw2_45"     "bw2_50"     "bw2_55"     "bw2_60"     "bw2_65"
## [41] "bw2_70"     "bw2_75"     "bw2_80"     "bw3_20"     "bw3_25"
## [46] "bw3_30"     "bw3_35"     "bw3_40"     "bw3_45"     "bw3_50"
## [51] "bw3_55"     "bw3_60"     "bw3_65"     "bw3_70"     "bw3_75"
## [56] "bw3_80"     "token"
```

merge these two dataframe with same colums

```
merge_df <- rbind(Rclass_token[, same], Tclass[, same])
merge_df <- na.omit(merge_df)
```

```
barplot(table(merge_df$token))
```



the label are unbalanced

```
head(merge_df)
```

```
## # A tibble: 6 x 57
##   tokennum speaker  gender matchid  stress celex~1 sylla~2 sylls~3 syllend word
##      <int> <fct>    <fct>  <fct>    <fct>    <int> <fct>     <dbl>   <dbl> <fct>
## 1        1 Speaker1 Male   g_243;e~ 0          522 t@         0.18    0.28 Word~
## 2        2 Speaker1 Male   g_243;e~ ’         1634 ’b$n      61.7    61.9  Word~
## 3        3 Speaker1 Male   g_243;e~ 0          725 b@        65.2    65.4  Word~
## 4        4 Speaker1 Male   g_243;e~ ’           11 ’g$       66.6    67.0  Word~
## 5        5 Speaker1 Male   g_243;e~ ’        21107 ’w3       67.7    67.8  Word~
## 6        6 Speaker1 Male   g_243;e~ ’         1383 ’T3       68.2    68.4  Word~
## # ... with 47 more variables: wordstart <dbl>, wordend <dbl>, tokenstart <dbl>,
## #   tokenend <dbl>, corpusfreq <int>, howcoded <fct>, tokendur <dbl>,
## #   bw1_20 <dbl>, bw1_25 <dbl>, bw1_30 <dbl>, bw1_35 <dbl>, bw1_40 <dbl>,
## #   bw1_45 <dbl>, bw1_50 <dbl>, bw1_55 <dbl>, bw1_60 <dbl>, bw1_65 <dbl>,
## #   bw1_70 <dbl>, bw1_75 <dbl>, bw1_80 <dbl>, bw2_20 <dbl>, bw2_25 <dbl>,
## #   bw2_30 <dbl>, bw2_35 <dbl>, bw2_40 <dbl>, bw2_45 <dbl>, bw2_50 <dbl>,
## #   bw2_55 <dbl>, bw2_60 <dbl>, bw2_65 <dbl>, bw2_70 <dbl>, bw2_75 <dbl>, ...
## # i Use ‘colnames()‘ to see all variable names
```

```
num_token <- select_if(merge_df, is.numeric)
num_token$token <- merge_df$token
head(num_token)
```

```
## # A tibble: 6 x 50
##   tokennum celexfreq syllstart syllend wordstart wordend token~1 token~2 corpu~3
##      <int>     <int>     <dbl>   <dbl>     <dbl>   <dbl>   <dbl>   <dbl>   <int>
## 1        1       522      0.18    0.28      0.12    0.62    0.24    0.28      41
## 2        2      1634     61.7    61.9      61.7    61.9    61.7    61.9      117
## 3        3       725     65.2    65.4      64.7    65.4    65.2    65.4       13
## 4        4        11     66.6    67.0      66.6    67.0    66.7    67.0       95
## 5        5     21107     67.7    67.8      67.7    67.8    67.8    67.8     2442
## 6        6      1383     68.2    68.4      68.2    68.5    68.3    68.4      103
## # ... with 41 more variables: tokendur <dbl>, bw1_20 <dbl>, bw1_25 <dbl>,
## #   bw1_30 <dbl>, bw1_35 <dbl>, bw1_40 <dbl>, bw1_45 <dbl>, bw1_50 <dbl>,
## #   bw1_55 <dbl>, bw1_60 <dbl>, bw1_65 <dbl>, bw1_70 <dbl>, bw1_75 <dbl>,
## #   bw1_80 <dbl>, bw2_20 <dbl>, bw2_25 <dbl>, bw2_30 <dbl>, bw2_35 <dbl>,
## #   bw2_40 <dbl>, bw2_45 <dbl>, bw2_50 <dbl>, bw2_55 <dbl>, bw2_60 <dbl>,
## #   bw2_65 <dbl>, bw2_70 <dbl>, bw2_75 <dbl>, bw2_80 <dbl>, bw3_20 <dbl>,
## #   bw3_25 <dbl>, bw3_30 <dbl>, bw3_35 <dbl>, bw3_40 <dbl>, bw3_45 <dbl>, ...
## # i Use ‘colnames()‘ to see all variable names
```

scale the numeric variable

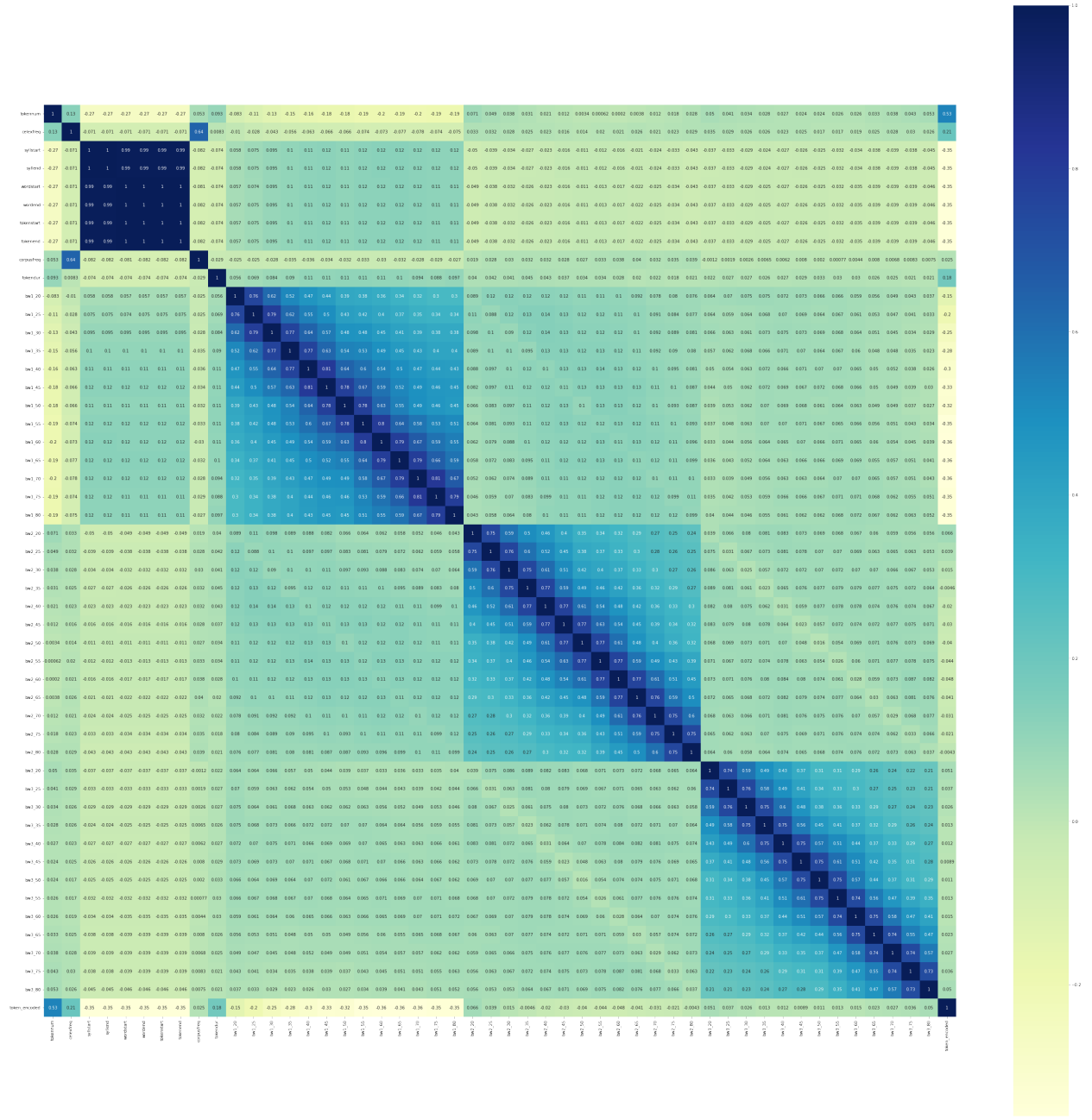
```
# Standardize the data
standardized_mergedata <- scale(num_token[, c(1:49)], center = TRUE, scale = TRUE)
num_token[, c(1:49)] <- standardized_mergedata
```

encode the token. r-1, t-0

```
num_token$token_encoded <- ifelse(num_token$token == 'r', 1, 0)
merge_cor <- cor(num_token[, c(1:49, 51)])
```

correlation map between variables(use python to draw it)

```
write_csv(as.data.frame(num_token[, c(1:49, 51)]), file = "merge_df.csv")
```



print all the variables name, whose correlations are higher than 0.9

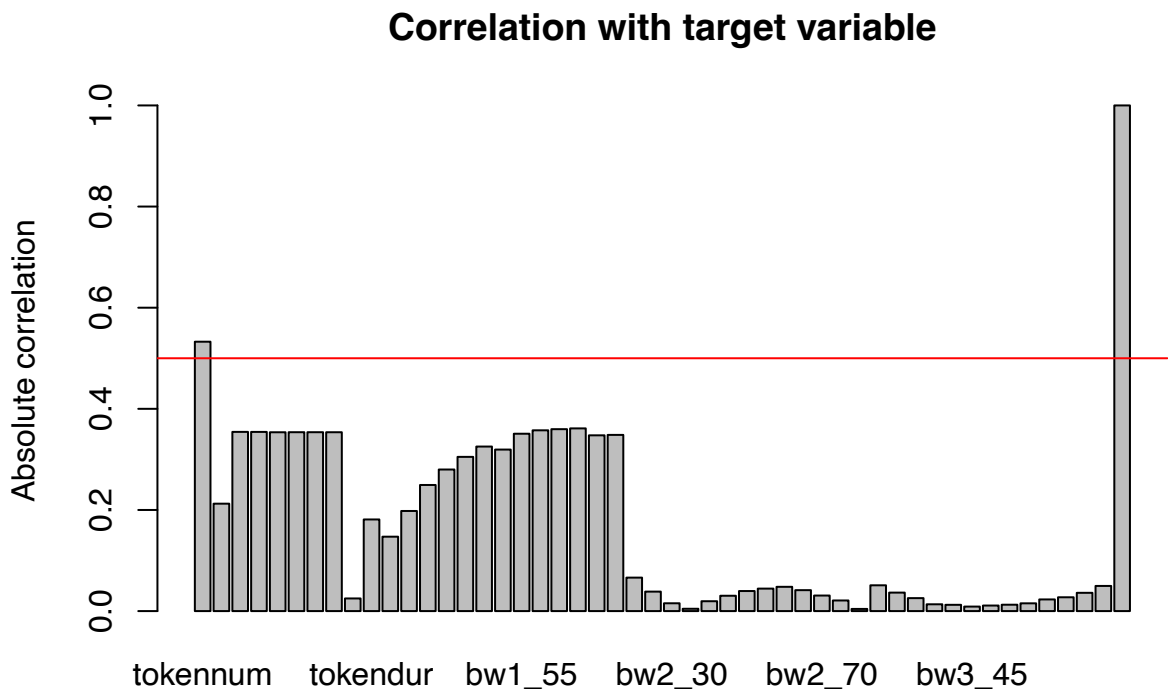
```
high_corr2 <- data.frame(var1 = character() , var2 = character(), cor = numeric())
z = 1
for (i in 1:50) {
```

```
  for (j in 1:i) {
    if (abs(merge_cor[i, j]) > 0.9 && i != j) {
      high_corr2[z, 1] <- colnames(merge_cor)[j]
      high_corr2[z, 2] <- colnames(merge_cor)[i]
      high_corr2[z, 3] <- merge_cor[i, j]
      z = z +1
    }
  }
}
high_corr2
```

```
##          var1       var2       cor
## 1   syllstart    syllend 0.9999999
## 2   syllstart  wordstart 0.9907643
## 3     syllend  wordstart 0.9907647
## 4   syllstart    wordend 0.9907647
## 5     syllend    wordend 0.9907653
## 6   wordstart    wordend 0.9999998
## 7   syllstart tokenstart 0.9907649
## 8     syllend tokenstart 0.9907654
## 9   wordstart tokenstart 0.9999999
## 10    wordend tokenstart 0.9999999
## 11  syllstart   tokenend 0.9907645
## 12    syllend   tokenend 0.9907651
## 13  wordstart   tokenend 0.9999998
## 14    wordend   tokenend 0.9999999
## 15 tokenstart   tokenend 0.9999999
```

for the correlation between variables and target

```
barplot(abs(merge_cor[, 50]), main = "Correlation with target variable", ylab = "Absolute correlation")
abline(h = 0.5, col = "red")
```




```
merge_cor_df <- as.data.frame(merge_cor)
head(merge_cor_df)
```

```
##             tokennum   celexfreq   syllstart     syllend   wordstart
## tokennum   1.0000000  0.12622317 -0.26666716 -0.26664952 -0.26636383
## celexfreq  0.1262232  1.00000000 -0.07123087 -0.07132948 -0.07110637
## syllstart -0.2666672 -0.07123087  1.00000000  0.99999985  0.99076432
## syllend   -0.2666495 -0.07132948  0.99999985  1.00000000  0.99076471
## wordstart -0.2663638 -0.07110637  0.99076432  0.99076471  1.00000000
## wordend   -0.2664148 -0.07137406  0.99076470  0.99076533  0.99999976
##               wordend  tokenstart    tokenend  corpusfreq     tokendur
## tokennum  -0.26641479 -0.26640901 -0.26637849  0.05308553  0.092704090
## celexfreq -0.07137406 -0.07123759 -0.07125554  0.64001510  0.008308352
## syllstart  0.99076470  0.99076494  0.99076450 -0.08180775 -0.074272734
## syllend    0.99076533  0.99076536  0.99076509 -0.08192476 -0.074079564
## wordstart  0.99999976  0.99999991  0.99999984 -0.08137903 -0.074125266
## wordend    1.00000000  0.99999986  0.99999992 -0.08164840 -0.073956194
##                bw1_20      bw1_25      bw1_30      bw1_35      bw1_40
## tokennum  -0.08301178 -0.10774826 -0.13368482 -0.15371226 -0.16470995
## celexfreq -0.01000265 -0.02846127 -0.04304287 -0.05602254 -0.06287913
## syllstart  0.05774585  0.07529451  0.09480663  0.10399363  0.11430654
## syllend    0.05775126  0.07530717  0.09482029  0.10400774  0.11432411
## wordstart  0.05709911  0.07447045  0.09453451  0.10340941  0.11462350
## wordend    0.05715179  0.07453856  0.09461156  0.10349239  0.11471399
##                bw1_45      bw1_50      bw1_55      bw1_60      bw1_65
```

```
## tokennum  -0.17776892 -0.17582381 -0.19407216 -0.19619835 -0.19370642
## celexfreq -0.06595692 -0.06572713 -0.07419592 -0.07265706 -0.07683835
## syllstart  0.11896894  0.11041069  0.12058766  0.12261137  0.12332538
## syllend    0.11898905  0.11043143  0.12060815  0.12263650  0.12334830
## wordstart  0.11849624  0.11025820  0.12057172  0.12225102  0.12292031
## wordend    0.11859308  0.11035335  0.12067062  0.12235429  0.12302323
##                bw1_70      bw1_75     bw1_80      bw2_20      bw2_25
## tokennum  -0.19794399 -0.19086765 -0.1899234  0.07137890  0.04895939
## celexfreq -0.07752644 -0.07447837 -0.0754227  0.03322598  0.03230431
## syllstart  0.11913874  0.11525554  0.1154944 -0.04982556 -0.03926407
## syllend    0.11915983  0.11527866  0.1155216 -0.04982175 -0.03926346
## wordstart  0.11870656  0.11427354  0.1148882 -0.04937254 -0.03807990
## wordend    0.11881136  0.11437924  0.1149968 -0.04937753 -0.03808427
##                bw2_30      bw2_35      bw2_40      bw2_45      bw2_50
## tokennum   0.03787788  0.03097908  0.02102057  0.01226560  0.00341216
## celexfreq  0.02770229  0.02545353  0.02264716  0.01646396  0.01398996
## syllstart -0.03378832 -0.02675691 -0.02280291 -0.01559208 -0.01081496
## syllend   -0.03379208 -0.02676122 -0.02280826 -0.01559930 -0.01082360
## wordstart -0.03248183 -0.02620927 -0.02267662 -0.01576303 -0.01113131
## wordend   -0.03248622 -0.02621072 -0.02267832 -0.01576207 -0.01113157
##                bw2_55        bw2_60       bw2_65      bw2_70      bw2_75
## tokennum   0.000615153  0.0002017475  0.003752653  0.01247119  0.01804350
## celexfreq  0.019539451  0.0214781281  0.026130384  0.02125110  0.02277750
## syllstart -0.012132562 -0.0164749616 -0.021418263 -0.02427605 -0.03331663
## syllend   -0.012142356 -0.0164905565 -0.021431175 -0.02428911 -0.03333028
## wordstart -0.012519019 -0.0169438934 -0.021588905 -0.02462119 -0.03363747
## wordend   -0.012518298 -0.0169475795 -0.021591170 -0.02462387 -0.03364069
##                bw2_80      bw3_20      bw3_25      bw3_30      bw3_35
## tokennum   0.02817396  0.04969308  0.04073739  0.03369148  0.02765857
## celexfreq  0.02870046  0.03479764  0.02914559  0.02605637  0.02588928
## syllstart -0.04253146 -0.03701013 -0.03297883 -0.02864128 -0.02445693
## syllend   -0.04254336 -0.03701442 -0.03297994 -0.02864034 -0.02445886
## wordstart -0.04284923 -0.03691591 -0.03310146 -0.02888397 -0.02526114
## wordend   -0.04285422 -0.03691907 -0.03309975 -0.02887842 -0.02525751
##                bw3_40      bw3_45      bw3_50      bw3_55      bw3_60
## tokennum   0.02666640  0.02358924  0.02419332  0.02602049  0.02552752
## celexfreq  0.02330098  0.02498030  0.01711503  0.01673983  0.01918719
## syllstart -0.02651951 -0.02579327 -0.02506965 -0.03168192 -0.03431759
## syllend   -0.02652062 -0.02579854 -0.02507134 -0.03168385 -0.03431868
## wordstart -0.02712898 -0.02637458 -0.02531881 -0.03172231 -0.03454167
## wordend   -0.02712228 -0.02637027 -0.02531231 -0.03171646 -0.03453523
##                bw3_65      bw3_70      bw3_75      bw3_80 token_encoded
## tokennum   0.03270611  0.03768054  0.04304405  0.05306184     0.5327371
## celexfreq  0.02520056  0.02765112  0.03000720  0.02603427     0.2124238
## syllstart -0.03814874 -0.03865564 -0.03843187 -0.04525579    -0.3543960
## syllend   -0.03815194 -0.03865708 -0.03843278 -0.04525398    -0.3543411
## wordstart -0.03860257 -0.03926068 -0.03907648 -0.04601838    -0.3536606
## wordend   -0.03859950 -0.03925697 -0.03907452 -0.04601602    -0.3537470
```

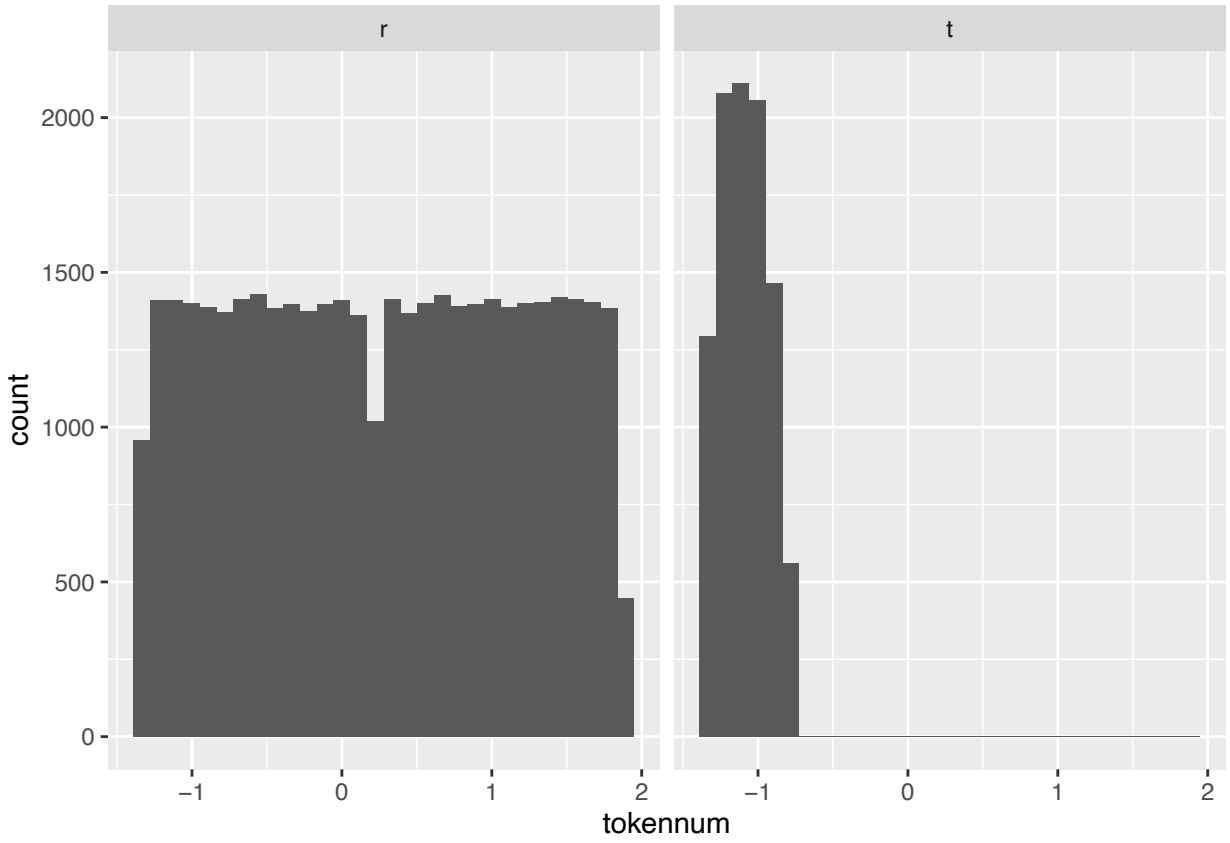
```
merge_cor_df$row <- colnames(merge_cor_df)
sqldf("SELECT row, token_encoded
      FROM merge_cor_df
      ORDER BY token_encoded DESC
      LIMIT 4")
```

```
##             row token_encoded
## 1 token_encoded     1.0000000
## 2      tokennum     0.5327371
## 3     celexfreq     0.2124238
## 4      tokendur     0.1811820
```

the distribution of variables with relatively high correlation with token

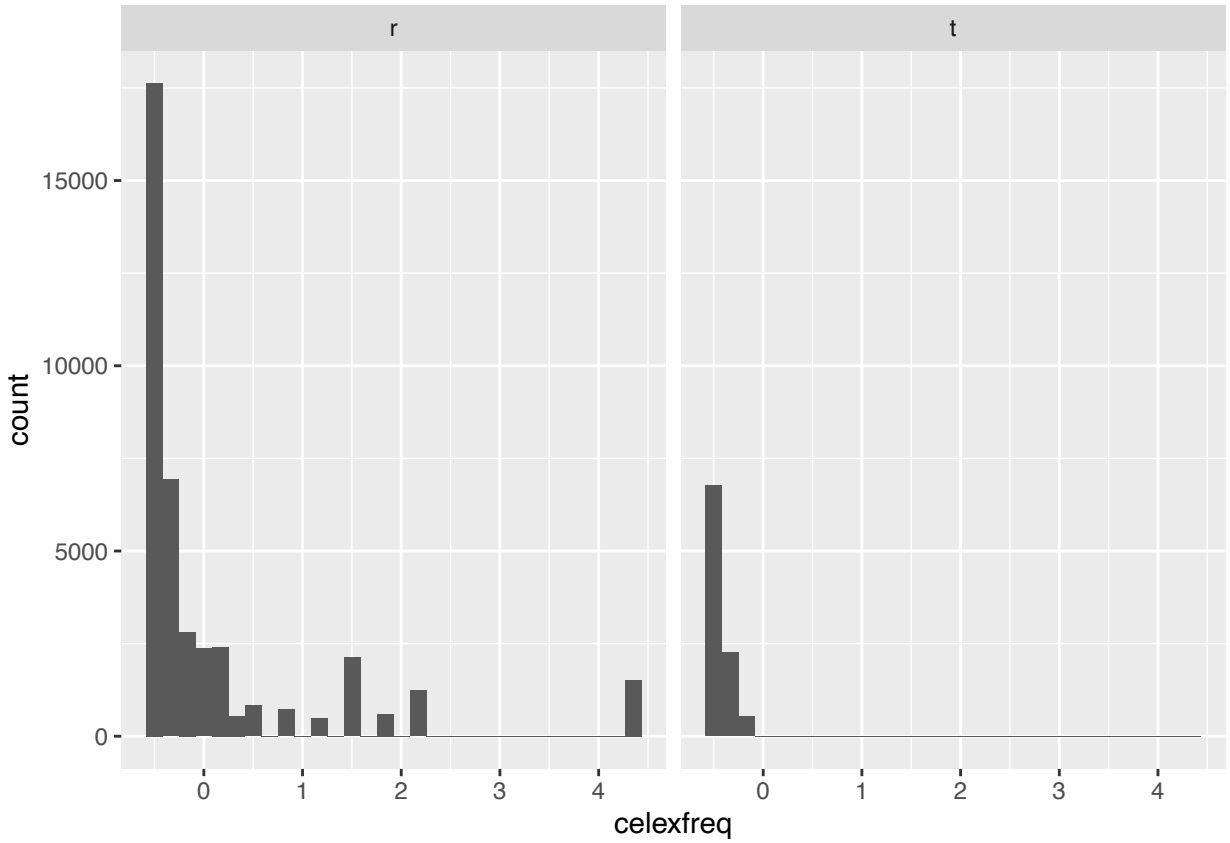
```
ggplot(data = num_token, aes(x = tokennum)) + geom_histogram() + facet_grid(.~token)
```

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




```
ggplot(data = num_token, aes(x = celexfreq)) + geom_histogram() + facet_grid(.~token)
```

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


r
t
15000
10000
5000
0
count
0
1
2
3
4
celexfreq

Reference:

[1] Villarreal, D. & Clark, L. & Hay, J. & Watson, K., (2020) “From categories to gradience: Auto-coding sociophonetic variation with random forests”, *Laboratory Phonology* 11(1): 6. doi: https://doi.org/10.5334/labphon.216

[2] https://github.com/nzilbb/How-to-Train-Your-Classifier