Group 304: R outputs
Fake Job Posting Prediction

- **Preprocessing of Data**

  i. Elimination of unused variable

```
> job_posting=job_posting[,-c(1,2,3,4,16,17)]
> colnames(job_posting)
 [1] "salary_range"        "company_profile"     "description"         "requirements"        "benefits"
 [6] "telecommuting"       "has_company_logo"    "has_questions"       "employment_type"     "required_experience"
[11] "required_education"  "fraudulent"
> 
```

  ii. Replacing empty values with 'NA'

```
> job_posting = read.csv("fake_job_postings.csv",header=T)
> job_posting[job_posting==""] <- NA
> 
```

  iii. Converting nominal variable to binary variable and creating N-1 dummy variables

```
> library(dummies)
> job_posting=dummy.data.frame(job_posting,names=c("employment_type"))
Warning message:
In model.matrix.default(~x - 1, model.frame(~x - 1), contrasts = FALSE) :
  non-list contrasts argument ignored
> colnames(job_posting)
 [1] "salary_range"              "company_profile"           "description"               "requirements"
 [5] "benefits"                  "telecommuting"             "has_company_logo"          "has_questions"
 [9] "employment_typeContract"   "employment_typeFull-time"  "employment_typeOther"      "employment_typePart-time"
[13] "employment_typeTemporary"  "employment_typeNA"         "required_experience"       "required_education"
[17] "fraudulent"
> #To drop one variable so that we have N-1 dummy variables
> job_posting=job_posting[,-c(14)]
> 
```

iv. Assigning variables

```
> x1 <- job_posting$description
> x2 <- job_posting$telecommuting
> x3 <- job_posting$has_company_logo
> x4 <-job_posting$has_questions
> x5 <- job_posting$employment_typeContract
> x6 <- job_posting$`employment_typeFull-time`
> x7 <- job_posting$employment_typeOther
> x8 <- job_posting$`employment_typePart-time`
> x9 <- job_posting$employment_typeTemporary
> x10 <- job_posting$fraudulent
>
```

v. R reads labels as nominal variables. To convert it into numeric, we use the factor function.

```
> x10f <- factor(x10)
>
```

- **Two Sample Hypothesis Testing**

```
>
> x2 = job_posting$fraudulent
> x1= job_posting$has_questions
> table(x1,x2)
   x2
x1     0    1
  0 8472  616
  1 8542  250
```

1. There are 8472 job postings for which ‘has_questions’=0 and are genuine.
2. There are 8542 job postings for which ‘has_questions’=1 and are genuine.
3. There are 616 job postings for which ‘has_questions’=0 and are fake.
4. There are 250 job postings for which ‘has_questions’=1 and are fake.

Null Hypothesis H_0: The proportion of job postings with 'has_questions'=1 and are fake = 0.048 (Have used proportion instead of mean because it is binary data)
Alternate Hypothesis H_a: The proportion of job postings with 'has_questions'=1 and are fake is not equal to 0.048.

```
> z.test <- prop.test(x=c(250,616),n=c(17880,17880),alternative="two.sided",correct=FALSE)
> z.test

	2-sample test for equality of proportions without continuity correction

data:  c(250, 616) out of c(17880, 17880)
X-squared = 158.52, df = 1, p-value < 2.2e-16
alternative hypothesis: two.sided
95 percent confidence interval:
 -0.02364924 -0.01729035
sample estimates:
   prop 1    prop 2
0.0139821 0.0344519
```

p-value < 0.05. Hence, null hypothesis rejected.

- **KNN Model**

Pre-processing of column 'description'

```
> library(tm)
> corpus_object <- Corpus(VectorSource(x1))
> corpus_object <- tm_map(corpus_object, removePunctuation)
Warning message:
In tm_map.SimpleCorpus(corpus_object, removePunctuation) :
  transformation drops documents
> corpus_object <- tm_map(corpus_object, removeWords, stopwords(kind = "en"))
Warning message:
In tm_map.SimpleCorpus(corpus_object, removeWords, stopwords(kind = "en")) :
  transformation drops documents
> corpus_object <- tm_map(corpus_object, stemDocument)
Warning message:
In tm_map.SimpleCorpus(corpus_object, stemDocument) :
  transformation drops documents
> #Converting all the remaining high frequency words to a DocumentTermMatrix
> frequencies <- DocumentTermMatrix(corpus_object)
> sparse_data_desc <- removeSparseTerms(frequencies, 0.995)
> sparse_data_jpdesc <- as.data.frame(as.matrix(sparse_data_desc))
> colnames(sparse_data_jpdesc) <- make.names(colnames(sparse_data_jpdesc))
> sparse_data_jpdesc$fraudulent <- job_posting$fraudulent
> colnames(sparse_data_jpdesc) <- make.unique(colnames(sparse_data_jpdesc), sep = "_")
> set.seed(2000)
> sparse_data_jpdesc$fraudulent=factor(sparse_data_jpdesc$fraudulent)
>
```

For k=151

```
> library(caret)
Warning message:
package ‘caret’ was built under R version 3.6.3
> select.data = sample (1:nrow(sparse_data_jpdesc),0.8*nrow(sparse_data_jpdesc))
> #without labels
> train.jp <- sparse_data_jpdesc[-select.data,]
> test.jp <- sparse_data_jpdesc[select.data,]
> #with Labels
> train.fr <- sparse_data_jpdesc$fraudulent[-select.data]
> test.fr <- sparse_data_jpdesc$fraudulent[select.data]
> library(class)
Warning message:
package ‘class’ was built under R version 3.6.3
> knn.151 <- knn(train.jp,test.jp,train.fr,k=151)
>
```

```
> confusionMatrix((table(knn.151 ,test.fr)))
Confusion Matrix and Statistics

       test.fr
knn.151     0     1
      0 13612   692
      1     0     0

               Accuracy : 0.9516
                 95% CI : (0.948, 0.9551)
    No Information Rate : 0.9516
    P-Value [Acc > NIR] : 0.5101

                  Kappa : 0

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 1.0000
            Specificity : 0.0000
         Pos Pred Value : 0.9516
         Neg Pred Value :    NaN
             Prevalence : 0.9516
         Detection Rate : 0.9516
   Detection Prevalence : 1.0000
      Balanced Accuracy : 0.5000

       'Positive' Class : 0
```

Accuracy = 95.16%

For k=71

```
> library(class)
Warning message:
package ‘class’ was built under R version 3.6.3
> knn.71 <- knn(train.jp,test.jp,train.fr,k=71)
>
```

```
> library(caret)
> confusionMatrix((table(knn.71 ,test.fr)))
Confusion Matrix and Statistics

      test.fr
knn.71     0     1
     0 13612   692
     1     0     0

               Accuracy : 0.9516
                 95% CI : (0.948, 0.9551)
    No Information Rate : 0.9516
    P-Value [Acc > NIR] : 0.5101

                  Kappa : 0

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 1.0000
            Specificity : 0.0000
         Pos Pred Value : 0.9516
         Neg Pred Value :    NaN
             Prevalence : 0.9516
         Detection Rate : 0.9516
   Detection Prevalence : 1.0000
      Balanced Accuracy : 0.5000

       'Positive' Class : 0
```

Accuracy = 95.16%

For k=27

```
> knn.27 <- knn(train.jp,test.jp,train.fr,k=27)
> library(caret)
> confusionMatrix((table(knn.27 ,test.fr)))
Confusion Matrix and Statistics

      test.fr
knn.27     0     1
     0 13610   688
     1     2     4

               Accuracy : 0.9518
                 95% CI : (0.9481, 0.9552)
    No Information Rate : 0.9516
    P-Value [Acc > NIR] : 0.479

                  Kappa : 0.0106

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.99985
            Specificity : 0.00578
         Pos Pred Value : 0.95188
         Neg Pred Value : 0.66667
             Prevalence : 0.95162
         Detection Rate : 0.95148
   Detection Prevalence : 0.99958
      Balanced Accuracy : 0.50282

       'Positive' Class : 0
```

Accuracy= 95.18%

For k=5

```
> select.data = sample (1:nrow(sparse_data_jpdesc),0.8*nrow(sparse_data_jpdesc))
> #Without labels
> train.jp <- sparse_data_jpdesc[-select.data,]
> test.jp <- sparse_data_jpdesc[select.data,]
> #With Labels
> train.fr <- sparse_data_jpdesc$fraudulent[-select.data]
> test.fr <- sparse_data_jpdesc$fraudulent[select.data]
> knn.5 <- knn(train.jp,test.jp,train.fr,k=5)
> library(caret)
> confusionMatrix((table(knn.5 ,test.fr)))
Confusion Matrix and Statistics

     test.fr
knn.5     0     1
    0 13546   439
    1    75   244

               Accuracy : 0.9641
                 95% CI : (0.9609, 0.9671)
    No Information Rate : 0.9523
    P-Value [Acc > NIR] : 2.785e-12

                  Kappa : 0.4709

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9945
            Specificity : 0.3572
         Pos Pred Value : 0.9686
         Neg Pred Value : 0.7649
             Prevalence : 0.9523
         Detection Rate : 0.9470
   Detection Prevalence : 0.9777
      Balanced Accuracy : 0.6759

       'Positive' Class : 0
```

Accuracy =96.41%

- <u>**Logistic Regression Model**</u>

```
> #Logistic Regression Model
> fit <- glm(x10f ~ x2+x3+x4+x5+x6+x7+x8+x9 , data=train.data, family=binomial())
> summary(fit)

Call:
glm(formula = x10f ~ x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9, family = binomial(),
    data = train.data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.0677  -0.2547  -0.2058  -0.1663   3.0339

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.30937    0.07883 -16.610  < 2e-16 ***
x2           0.56391    0.14490   3.892 9.95e-05 ***
x3          -2.10267    0.07779 -27.029  < 2e-16 ***
x4          -0.43047    0.08198  -5.251 1.51e-07 ***
x5          -0.74964    0.17236  -4.349 1.37e-05 ***
x6          -0.43213    0.08532  -5.065 4.09e-07 ***
x7           0.24118    0.28953   0.833  0.40484
x8           0.48182    0.14813   3.253  0.00114 **
x9          -1.84817    0.71908  -2.570  0.01016 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 6933.1  on 17879  degrees of freedom
Residual deviance: 5875.7  on 17871  degrees of freedom
AIC: 5893.7

Number of Fisher Scoring iterations: 7
```

```
> prob=predict(fit,type="response",newdata=test.data)
Warning message:
'newdata' had 3576 rows but variables found have 17880 rows
> #Cut-off value to calculate accuracy is 0.5
> for(i in 1:length(prob)){
+   if (prob[i] > 0.5){
+     prob[i]=1}
+   else {
+     prob[i]=0
+   }
+ }
> library(Metrics)
> accuracy(test.label,prob)
[1] 0.9549776
> |
```

Forward Selection Model:

```
> base=glm(x10f~x7, data=train.data, family=binomial())
> model1= step(base, scope=list(upper=fit,lower=~1),direction="both", trace=F)
> summary(model1)

Call:
glm(formula = x10f ~ x3 + x8 + x4 + x2 + x6 + x5 + x9, family = binomial(),
    data = train.data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.0673  -0.2564  -0.2059  -0.1664   3.0333

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.29745    0.07726 -16.793  < 2e-16 ***
x3          -2.10116    0.07775 -27.023  < 2e-16 ***
x8           0.46872    0.14714   3.186  0.00144 **
x4          -0.42902    0.08194  -5.236 1.64e-07 ***
x2           0.56409    0.14494   3.892 9.95e-05 ***
x6          -0.44499    0.08366  -5.319 1.04e-07 ***
x5          -0.76265    0.17152  -4.446 8.73e-06 ***
x9          -1.86121    0.71887  -2.589  0.00962 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 6933.1  on 17879  degrees of freedom
Residual deviance: 5876.3  on 17872  degrees of freedom
AIC: 5892.3

Number of Fisher Scoring iterations: 7
```

```
> prob=predict(model1,type="response",newdata=test.data)
Warning message:
'newdata' had 3576 rows but variables found have 17880 rows
> #Cut-off value to calculate accuracy is 0.5
> for(i in 1:length(prob)){
+   if (prob[i] > 0.5){
+     prob[i]=1}
+   else {
+     prob[i]=0
+   }
+ }
> library(Metrics)
> accuracy(test.label,prob)
[1] 0.9549776
```

Backward Selection Model:

```
> model2= step(fit,direction="backward",trace=F)
> summary(model2)

Call:
glm(formula = x10f ~ x2 + x3 + x4 + x5 + x6 + x8 + x9, family = binomial(),
    data = train.data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.0673  -0.2564  -0.2059  -0.1664   3.0333

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.29745    0.07726 -16.793  < 2e-16 ***
x2           0.56409    0.14494   3.892 9.95e-05 ***
x3          -2.10116    0.07775 -27.023  < 2e-16 ***
x4          -0.42902    0.08194  -5.236 1.64e-07 ***
x5          -0.76265    0.17152  -4.446 8.73e-06 ***
x6          -0.44499    0.08366  -5.319 1.04e-07 ***
x8           0.46872    0.14714   3.186  0.00144 **
x9          -1.86121    0.71887  -2.589  0.00962 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 6933.1  on 17879  degrees of freedom
Residual deviance: 5876.3  on 17872  degrees of freedom
AIC: 5892.3

Number of Fisher Scoring iterations: 7
```

```
> prob=predict(model2,type="response",newdata=test.data)
Warning message:
'newdata' had 3576 rows but variables found have 17880 rows
> #Cut-off value to calculate accuracy is 0.5
> for(i in 1:length(prob)){
+   if (prob[i] > 0.5){
+     prob[i]=1}
+   else {
+     prob[i]=0
+   }
+ }
> library(Metrics)
> accuracy(test.label,prob)
[1] 0.9549776
```

SVM Model

```
> model <- caret::train(y, x = job_posting[, colnames(job_posting) != 'fraudulent'], method = "svmLinear",
+                       trControl=trainControl(method = "cv", number = 10),
+                       tuneLength = 10)
> print(model)
Support Vector Machines with Linear Kernel

17880 samples
    8 predictor
    2 classes: '0', '1'

No pre-processing
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 16092, 16091, 16092, 16091, 16092, 16092, ...
Resampling results:

  Accuracy   Kappa
  0.9515661  0

Tuning parameter 'C' was held constant at a value of 1
```

Accuracy = 85.156%

Feature Extraction

Code execution on the genuine post description:

```
package ‘dplyr’ was built under R version 3.6.3
> description <- job_posting$description
> description <- as.character(description)
> Genuine_description <- filter(job_posting,fraudulent==0)
> description_G <- as.data.frame(Genuine_description$description)
> count <- seq(1, nrow(description_G), 1)
> lowerC_description_G <- sapply(count, function(c){tolower(description_G[c, 1])})
> library(stringr)
Warning message:
package ‘stringr’ was built under R version 3.6.3
> del_special_chars_description_G <- sapply(count, function(l){str_replace_all(lowerC_description_G[l], "[^[:alnum:]]", " ")})
> library(tm)
Loading required package: NLP
Warning message:
package ‘tm’ was built under R version 3.6.3
> del_special_chars_description_G <- VCorpus(VectorSource(del_special_chars_description_G))
> del_special_chars_description_G <- tm_map(del_special_chars_description_G, removeWords, stopwords(kind = "en"))
> del_special_chars_description_G <- tm_map(del_special_chars_description_G, removePunctuation)
> white_space_cleanup_description_G <- tm_map(del_special_chars_description_G, stripWhitespace)
> library(SnowballC)
Warning message:
package ‘SnowballC’ was built under R version 3.6.3
> stemming_description_G <- tm_map(white_space_cleanup_description_G, stemDocument)
> text_description_G <- tm_map(stemming_description_G, stemDocument,language = "english")
> docterm_corpus_description_G <- TermDocumentMatrix(text_description_G)
> review_Gen = removeSparseTerms(docterm_corpus_description_G, 0.99)
> findFreqTerms(review_Gen, 1000)
  [1] "abil"       "abl"       "account"   "accur"     "achiev"    "across"    "activ"     "addit"
  [9] "administr"  "advanc"    "adverti"   "agenc"     "also"      "amp"       "analysi"   "analyt"
 [17] "analyz"     "app"       "appli"     "applic"    "appropri"  "area"      "around"    "assign"
 [25] "assist"     "associ"    "autom"     "avail"     "back"      "base"      "benefit"   "best"
 [33] "big"        "brand"     "bring"     "build"     "busi"      "call"      "campaign"  "can"
```

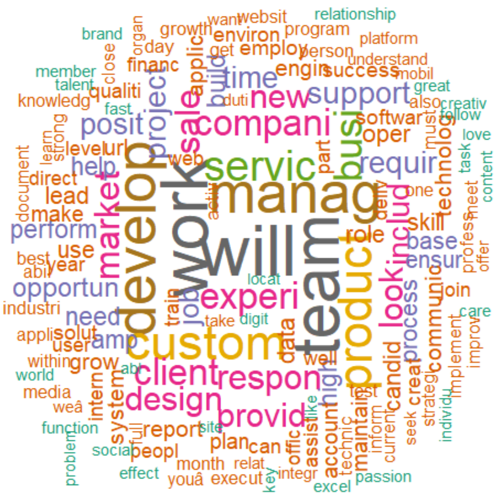
Creation of word cloud:

```
> description_matrix_G <- as.matrix(review_Gen)
> v_gen <- sort(rowSums(description_matrix_G),decreasing=TRUE)
> d_gen <- data.frame(word = names(v_gen),freq=v_gen)
> set.seed(2020)
> library(wordcloud)
Loading required package: RColorBrewer
Warning message:
package ‘wordcloud’ was built under R version 3.6.3
> wordcloud(words = d_gen$word, freq = d_gen$freq, min.freq = 1,
+           max.words=150, random.order=FALSE, rot.per=0.35,
+           colors=brewer.pal(8, "Dark2"))
>
```

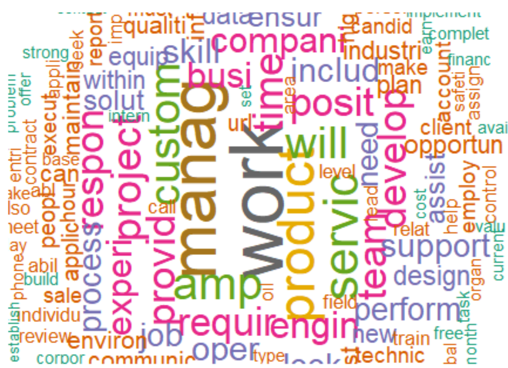
Code execution on the fake job post description:

```
>
> Fake_description <- filter(job_posting,fraudulent==1)
> description_F <- as.data.frame(Fake_description$description)
> count <- seq(1, nrow(description_F), 1)
> lowerC_description_F <- sapply(count, function(c){tolower(description_F[c, 1])})
> library(stringr)
> del_special_chars_description_F <- sapply(count, function(l){str_replace_all(lowerC_description_F[l], "[^[:alnum:]]", " ")})
> library(tm)
> del_special_chars_description_F <- VCorpus(VectorSource(del_special_chars_description_F))
> del_special_chars_description_F <- tm_map(del_special_chars_description_F, removeWords, stopwords(kind = "en"))
> del_special_chars_description_F <- tm_map(del_special_chars_description_F, removePunctuation)
> white_space_cleanup_description_F <- tm_map(del_special_chars_description_F, stripWhitespace)
> stemming_description_F <- tm_map(white_space_cleanup_description_F, stemDocument)
> text_description_F <- tm_map(stemming_description_F, stemDocument,language = "english")
> library(SnowballC)
> docterm_corpus_description_F <- TermDocumentMatrix(text_description_F)
> review_Fake = removeSparseTerms(docterm_corpus_description_F, 0.99)
> findFreqTerms(review_Fake, 1000)
[1] "manag" "work"
> description_matrix_F <- as.matrix(review_Fake)
> v_fake <- sort(rowSums(description_matrix_F),decreasing=TRUE)
> d_fake <- data.frame(word = names(v_fake),freq=v_fake)
> set.seed(2020)
> wordcloud(words = d_fake$word, freq = d_fake$freq, min.freq = 1,
+           max.words=150, random.order=FALSE, rot.per=0.35,
+           colors=brewer.pal(8, "Dark2"))
>
```

Below is the snapshot of the word cloud output for genuine and fake job postings.



Genuine Job Posting



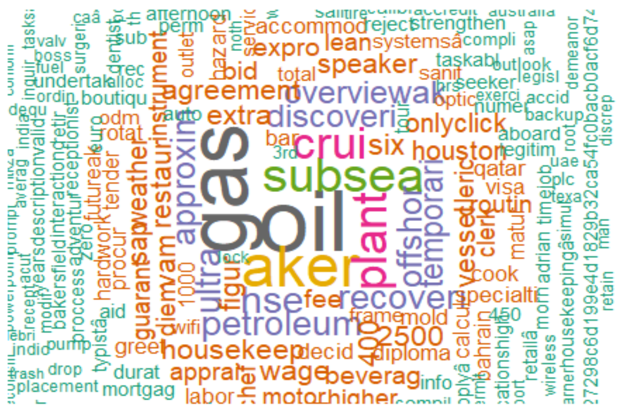
Fake Job Posting

Our next step would be to find the words that are present only in the fraudulent job postings and not in the genuine job postings.

Below is the snapshot of the code used for the same purpose.

```
>
> d_gen <- data.frame(lapply(d_gen, as.character), stringsAsFactors=FALSE)
> d_fake <- data.frame(lapply(d_fake, as.character), stringsAsFactors=FALSE)
> d_fake_notin_d <-   d_fake[!d_fake$word %in% d_gen$word, ]
> d_fake_notin_d <-   d_fake_notin_d[complete.cases(d_fake_notin_d), ]
> d_fake_notin_d$word <- as.factor(d_fake_notin_d$word)
> d_fake_notin_d$freq <- as.numeric(d_fake_notin_d$freq)
> set.seed(2020)
> wordcloud(words = d_fake_notin_d$word, freq = d_fake_notin_d$freq, min.freq = 5,
+           max.words=250, random.order=FALSE, rot.per=0.35,
+           colors=brewer.pal(8, "Dark2"))
Warning messages:
```

The word cloud of the words that are present in fake job postings but not in the genuine job postings is given below:



From the above output, we can say that the words gas, oil, crui, aker, subsea, plant, offshor, temporari are present in the description of the fake job postings but not in genuine job postings.