Random For(r)est

Sebastian Heilmann

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1 Explore data

In this script, we will use linguistic features to predict the speaker (Forrest Gump vs anyone else) of spoken lines in the movie “Forrest Gump” by Robert Zemeckis.

Let’s start by exploring some sentences.

```
as.tbl(head(forrest))
```

```
## # A tibble: 6 x 32
##   run   onset duration offset time_to_next overlapping person FG    kind
##   <chr> <dbl>    <dbl>  <dbl> <chr>        <chr>       <chr>  <chr> <chr>
## 1 run-1  1207     1.4    2607 1.96         False       ERZAE… 1     spee…
## 2 run-1  3167     3.84   7007 4.16         False       ERZAE… 1     spee…
## 3 run-1  7327     1.6    8927 2.08         False       ERZAE… 1     spee…
## 4 run-1  9407     0.68  10087 6.6          False       ERZAE… 1     spee…
## 5 run-1 16007     3.48  19487 4.76         False       ERZAE… 1     spee…
## 6 run-1 20767   145.   165567 2.08         False       OST    1     song
## # … with 23 more variables: prosody <chr>, sentence_grammar <chr>, text <chr>,
## #   comp_score <dbl>, word_count <int>, lexfreq_norm_log_sum <dbl>,
## #   lexfreq_norm_log_mean <dbl>, lexmin <dbl>, lexmax <dbl>, sent_sum <dbl>,
## #   isforrest <chr>, satzid <fct>, open <int>, closed <int>, undefined <int>,
## #   document <chr>, CTTR <dbl>, n_lowers <dbl>, n_caps <dbl>, n_uq_words <dbl>,
## #   n_uq_chars <dbl>, n_charsperword <dbl>, depth <dbl>
```

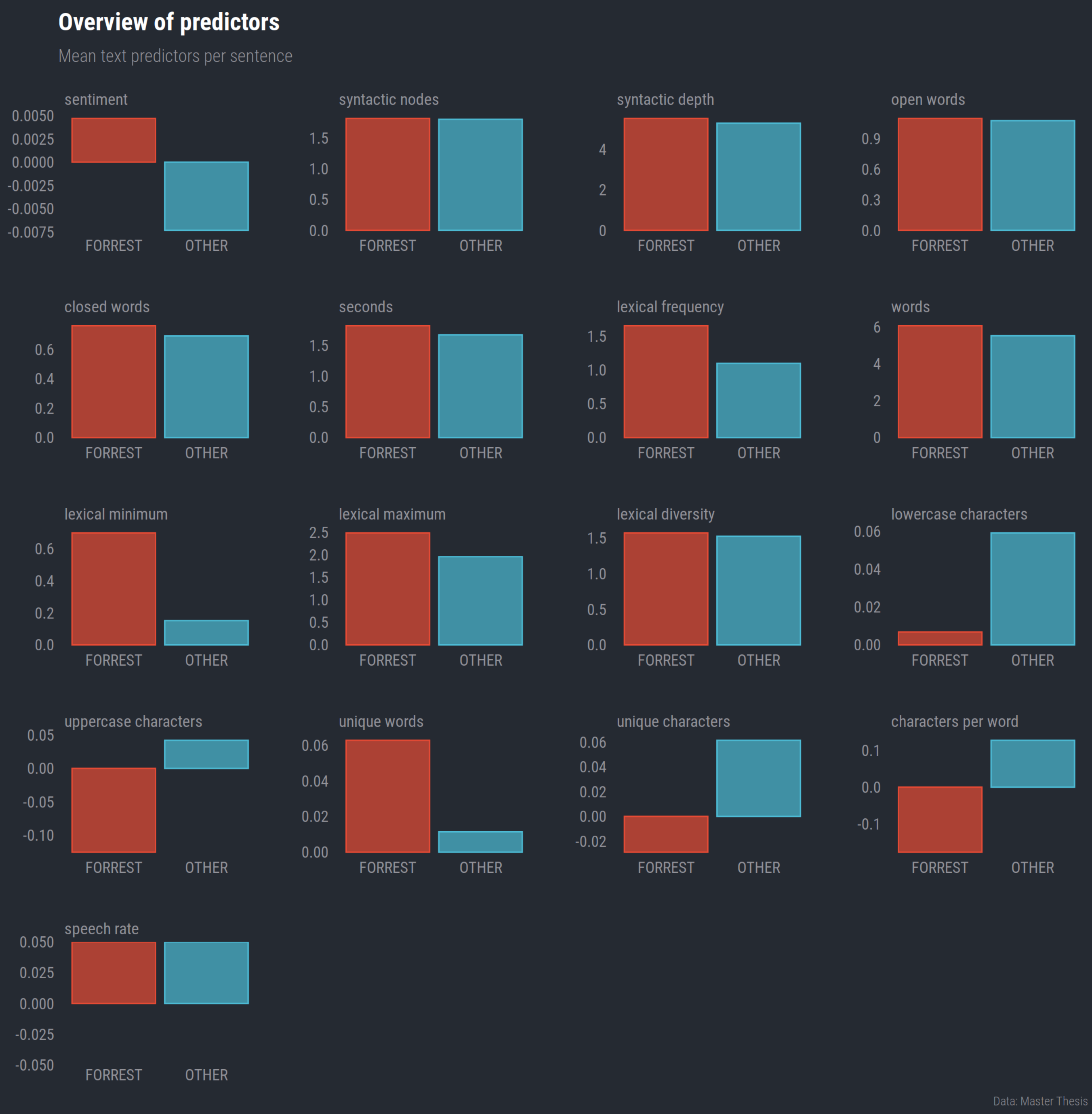
```
set.seed(51)
forrest %>%
  filter(!is.na(isforrest)) %>%
  group_by(isforrest) %>%
  sample_n(4) %>%
  select(isforrest, text)
```

```
## # A tibble: 8 x 2
## # Groups:   isforrest [2]
##   isforrest text
##   <chr>     <chr>
## 1 FORREST   Wir waren wie eine Familie
## 2 FORREST   Und das Abendessen
## 3 FORREST   Wir waren wie Pech und Schwefel
## 4 FORREST   Sie wollte dass ich die beste Schulbildung bekomme
## 5 OTHER     Es ist hell
## 6 OTHER     Everybodys Talkin
## 7 OTHER     Denk immer an das was ich dir gesagt habe
## 8 OTHER     Sie trägt noch ihr türkisfarbenes Kellnerinnen-Kleid
```

We have a lot of features! But let’s also try to take the sentence length into account and recalculate / add some features.

```
forrest <- forrest %>%
  mutate(sentiment = sent_sum / word_count,
         nodes = comp_score / word_count,
         open_words = open / word_count,
         closed_words = closed / word_count,
         speech_rate = word_count / duration)
```

Starting with exploratory data analysis is always important before modeling. Let’s therefore make one nice plot to explore the relationships in this data. Are there any text features that distinguish Forrest Gump from other speakers?



We can see differences in lexical features and character-features especially. We will now create a seperate data set with those variables.

```
# select relevant variables
forrest_clean <- forrest_clean %>%
  select(c(CTTR:speech_rate, duration, word_count, lexfreq_norm_log_mean:lexmax,isforrest)) %>%
  filter(!is.infinite(speech_rate)) %>%
  na.omit()
```

2 Build a random forest model

2.1 Split data into training and test data set

We will start by splitting our data into a training and testing set. Then we will create cross-validation resamples of the training data to evaluate our models.

```
set.seed(123)
forrest_split <- initial_split(forrest_clean, strata = isforrest)
forrest_train <- training(forrest_split)
forrest_test <- testing(forrest_split)

set.seed(123)
forrest_folds <- vfold_cv(forrest_train, strata = isforrest)
```

2.2 Define a tidmodel recipe and workflow.

We now want to tune some hyperparameters. Because we use a random forest model, we don't need to do much preprocessing. That means, that we don't need to worry about centering or scaling our data.

```
forrest_recipe <-
  recipe(isforrest ~ ., data = forrest_clean) %>%
  step_naomit(all_predictors()) %>%
  step_zv(all_predictors())

rf_model <-
  # specify that the model is a random forest
  rand_forest() %>%
  # specify parameters that we want to tune
  set_args(mtry = tune(), trees = tune(), min_n = tune()) %>%
  # select the engine that underlies the model
  set_engine("ranger", importance = "impurity") %>%
  # choose binary classification mode
  set_mode("classification")
rf_model
```

```
## Random Forest Model Specification (classification)
##
## Main Arguments:
##   mtry = tune()
##   trees = tune()
##   min_n = tune()
##
## Engine-Specific Arguments:
##   importance = impurity
##
## Computational engine: ranger
```

```
rf_workflow <- workflow() %>%
  # add the recipe
  add_recipe(forrest_recipe) %>%
  # add the model
  add_model(rf_model)

rf_workflow
```

```
## ══ Workflow ════════════════════════════════════════════════════════════════════════════
## Preprocessor: Recipe
## Model: rand_forest()
##
## ── Preprocessor ────────────────────────────────────────────────────────────────────────
## 2 Recipe Steps
##
## ● step_naomit()
## ● step_zv()
##
## ── Model ───────────────────────────────────────────────────────────────────────────────
## Random Forest Model Specification (classification)
##
## Main Arguments:
##   mtry = tune()
##   trees = tune()
##   min_n = tune()
##
## Engine-Specific Arguments:
##   importance = impurity
##
## Computational engine: ranger
```

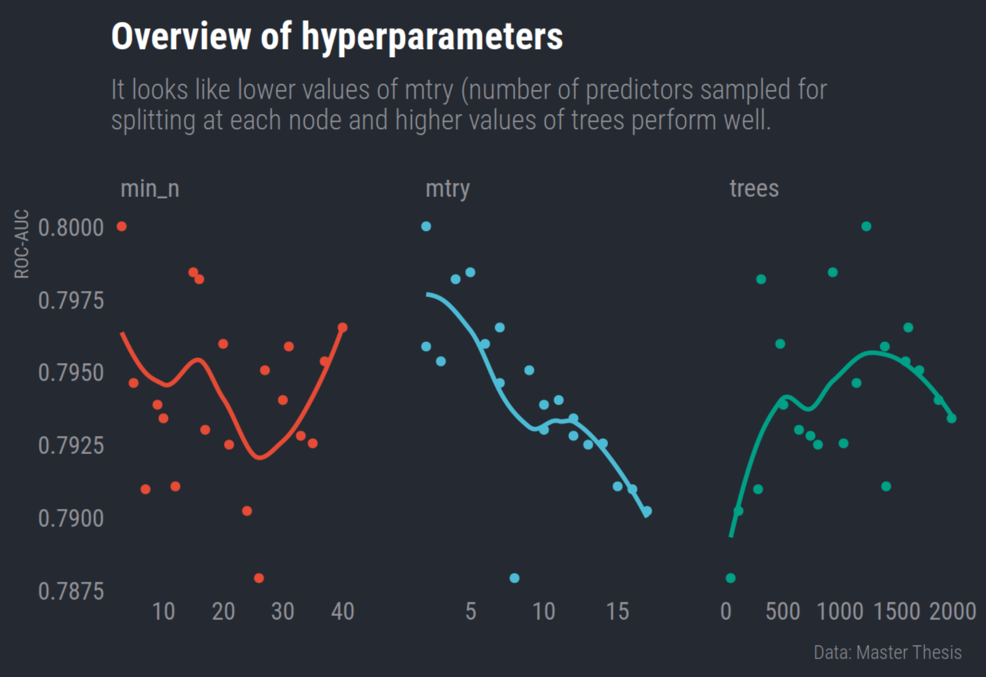
2.3 Tune hyperparameters

We will use tune_grid() with our tuneable workflow (and our grid of parameters (mtry, trees, min_n) and our resamples to try. Most importantly, but optional, we will call doParallel::registerDoParallel() to parallelize R code on our machine.

```
doParallel::registerDoParallel()

set.seed(234)
tune_res <- tune_grid(
  rf_workflow,
  resamples = forrest_folds,
  grid = 20
)
```

Let's try a visualization to understand our results.



What are the best performing sets of parameters?

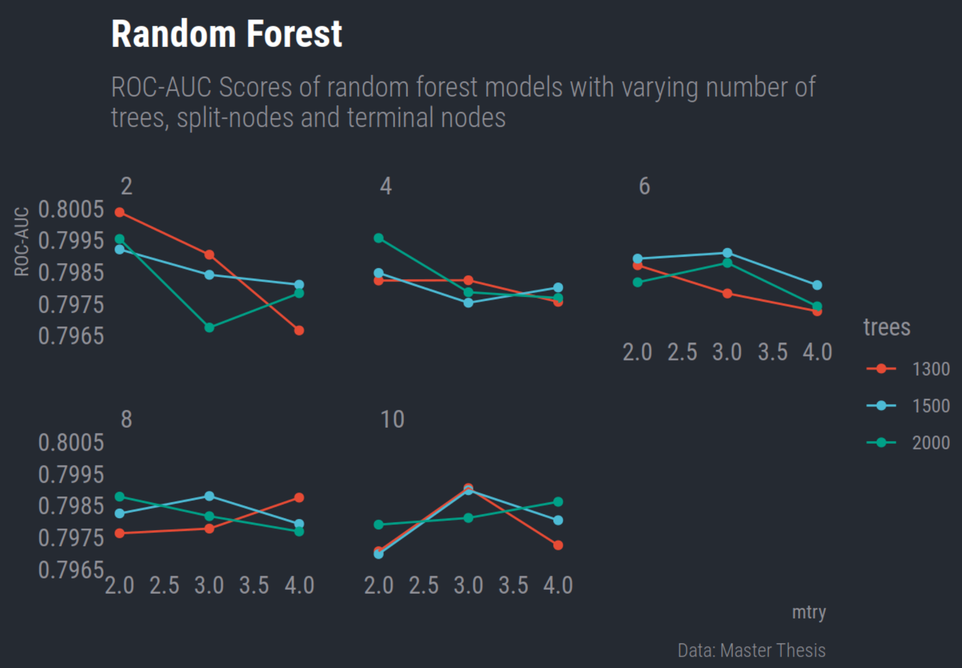
```
show_best(tune_res, "roc_auc")
```

```
## # A tibble: 5 x 9
##    mtry trees min_n .metric .estimator  mean     n std_err .config
##   <int> <int> <int> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
## 1     2  1236     3 roc_auc binary     0.800    10 0.00649 Model12
## 2     5   940    15 roc_auc binary     0.798    10 0.00644 Model11
## 3     4   310    16 roc_auc binary     0.798    10 0.00620 Model03
## 4     7  1605    40 roc_auc binary     0.797    10 0.00623 Model01
## 5     6   478    20 roc_auc binary     0.796    10 0.00648 Model05
```

We will tune our hyperparameters once more, but in a more fine grained way.

```
set.seed(123)
# set tuning parameters to try
rf_grid <- expand.grid(mtry = c(2,3,4), trees = c(1300, 1500, 2000), min_n = c(4,6,8,10,20,30,32,34,36))
# apply model and extract results
rf_tune_results <- rf_workflow %>%
  tune_grid(resamples = forrest_folds,
            grid = rf_grid,
            # choose some metrics
            metrics = metric_set(accuracy, roc_auc, sens, spec)
  )
```

Let's have a look at all combinations of parameters.



3 Finalize the workflow and evaluate the test set

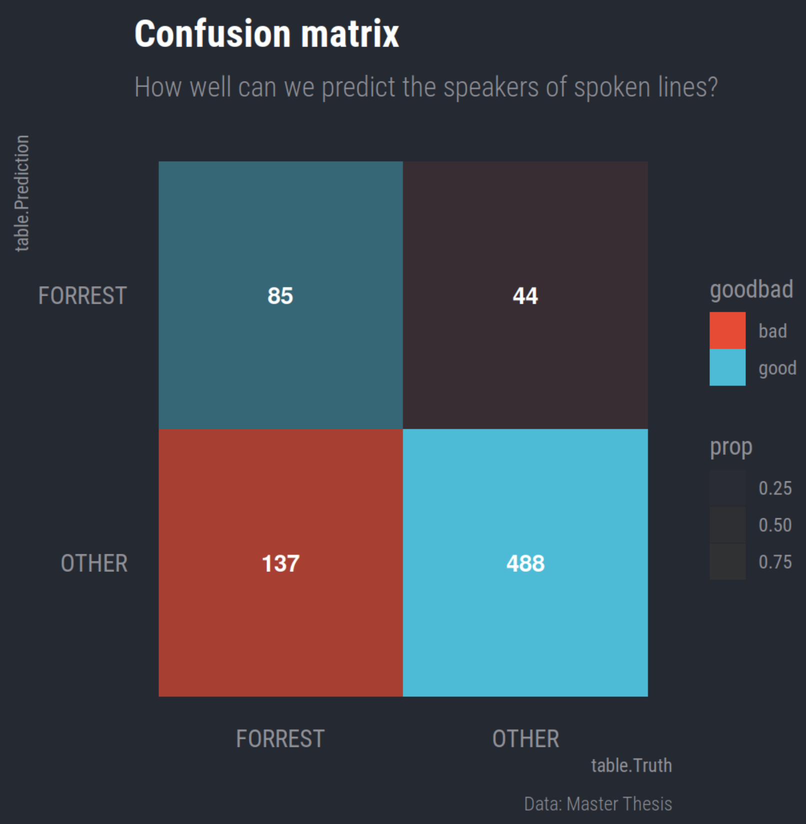
```r
param_final <- rf_tune_results %>% select_best(metric = "roc_auc")
rf_workflow <- rf_workflow %>% finalize_workflow(param_final)
```

```r
# fit on the training set and evaluate on test set
rf_fit <- rf_workflow %>% last_fit(forrest_split)
# check performance on test set
test_performance <- rf_fit %>% collect_metrics()
# generate predictions from the test set
test_predictions <- rf_fit %>% collect_predictions()
# create confusion matrix
confusion_matrix <- test_predictions %>% conf_mat(truth = isforrest, estimate = .pred_class)
confusion_matrix <- as.data.frame(confusion_matrix["table"])
```

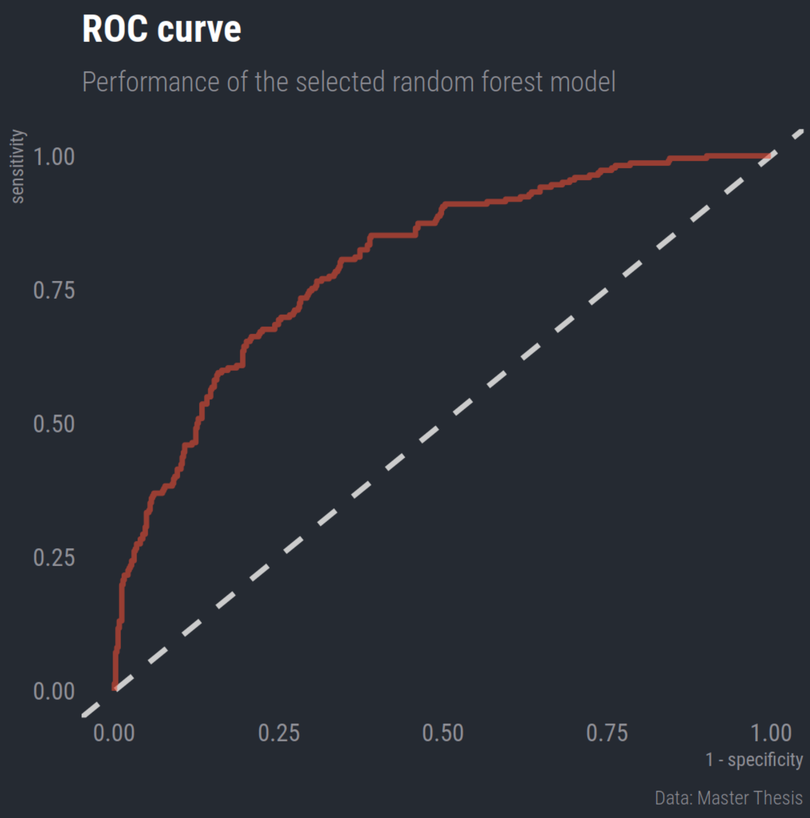
One way to visualize the perfomance of a classification model is to use a confusion matrix.

```r
plotTable <- confusion_matrix %>%
  mutate(goodbad = ifelse(confusion_matrix$table.Prediction == confusion_matrix$table.Truth, "good", "bad")) %>%
  group_by(table.Truth) %>%
  mutate(prop = table.Freq/sum(table.Freq))

ggplot(data = plotTable, mapping = aes(x = table.Truth, y = table.Prediction, fill = goodbad, alpha = prop)) +
  geom_tile() +
  geom_text(aes(label = table.Freq), vjust = .5, fontface  = "bold", alpha = 1, color = "white") +
  theme_minimal() +
  ylim(rev(levels(confusion_matrix$table.Prediction))) +
  theme_ft_rc() +
  labs(title = "Confusion matrix",
       subtitle = "How well can we predict the speakers of spoken lines?",
       caption = "Data: Master Thesis") +
  theme(panel.border = element_blank(),
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank()) +
  scale_fill_npg(alpha = 1) +
  scale_color_npg()
```




```
test_predictions %>%
  group_by(id) %>%
  roc_curve(isforrest, .pred_FORREST) %>%
  ggplot(aes(1 - specificity, sensitivity, color = id)) +
  geom_abline(lty = 2, color = "gray80", size = 1.2) +
  geom_path(show.legend = FALSE, alpha = 0.6, size = 1.2) +
    labs(title = "ROC curve",
         subtitle = "Performance of the selected random forest model",
         caption = "Data: Master Thesis") +
    theme_minimal() +
    theme_ft_rc() +
    theme(panel.border = element_blank(),
          panel.grid.major = element_blank(),
          panel.grid.minor = element_blank()) +
    scale_fill_npg() +
    scale_color_npg()
```



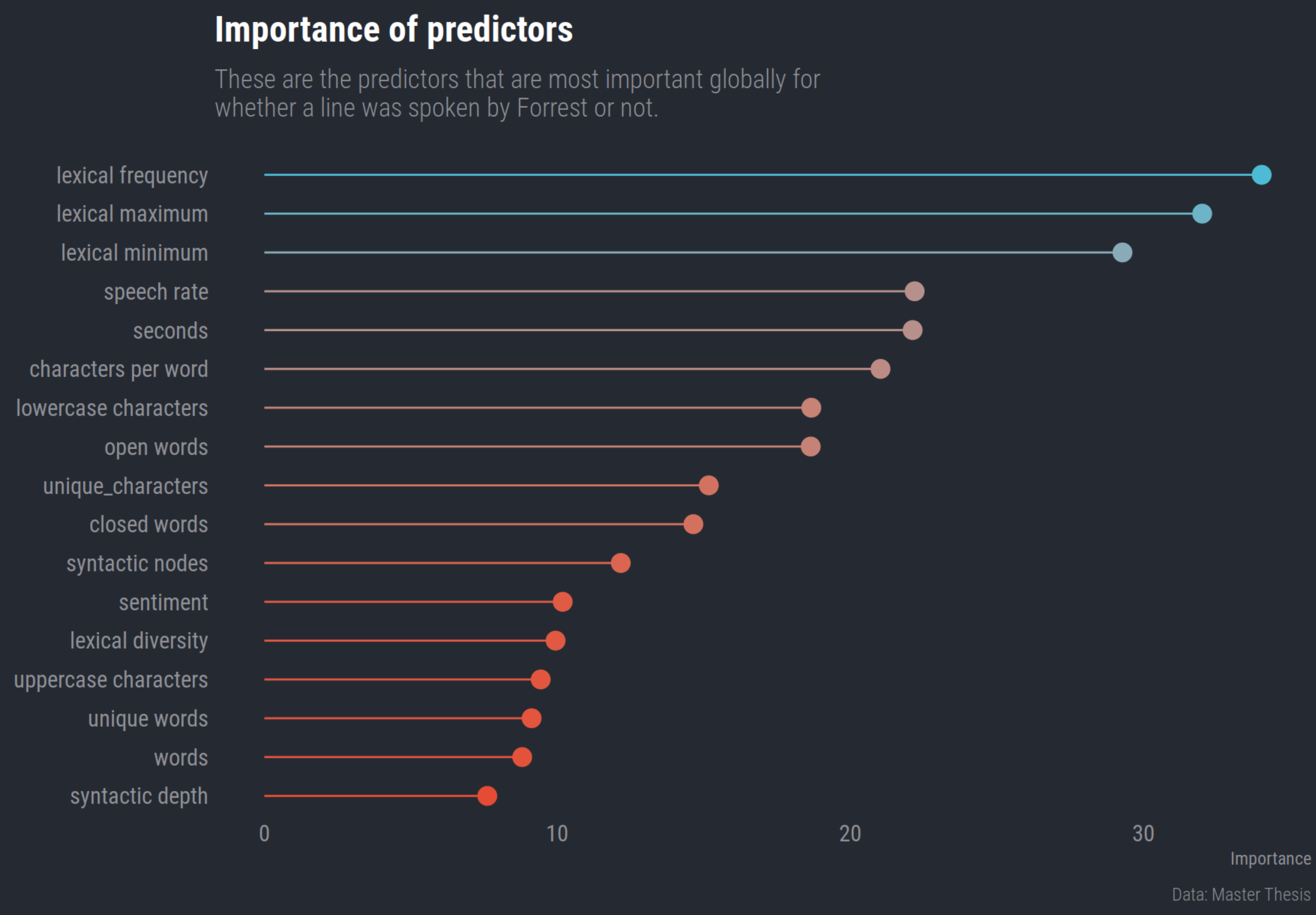
Our results here indicate that we did not overfit during the tuning process. We can also create a ROC curve for the testing set.

4 Extract important features

```
library(vip)
imp_df <- rf_workflow %>%
  fit(data = forrest_test) %>%
  pull_workflow_fit() %>%
  vi()

# rename variables for plotting
imp_df$Variable <- c("lexical frequency",
                     "lexical maximum",
                     "lexical minimum",
                     "speech rate",
                     "seconds",
                     "characters per word",
                     "lowercase characters",
                     "open words",
                     "unique_characters",
                     "closed words",
                     "syntactic nodes",
                     "sentiment",
                     "lexical diversity",
                     "uppercase characters",
                     "unique words",
                     "words",
                     "syntactic depth")

imp_df$Variable <- as.factor(imp_df$Variable)
```


Importance of predictors
These are the predictors that are most important globally for
whether a line was spoken by Forrest or not.
lexical frequency
lexical maximum
lexical minimum
speech rate
seconds
characters per word
lowercase characters
open words
unique_characters
closed words
syntactic nodes
sentiment
lexical diversity
uppercase characters
unique words
words
syntactic depth
0
10
20
30
Importance
Data: Master Thesis