Evaluation of textmodels

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1 Summary

We obtain the highest accuracy of 77.1% using the pretrained Transformers model GBERT fine-tuned with our labeled dataset. It requires ~8 minutes of computing time using 4 training epochs (remote, Colab Pro).

The Superlearner ensemble of single supervised classifiers obtains 71.2% accuracy (w/o cross-validation!), using the tfidf-transformed dfm. It requires ~18 minutes (w/o cross-validation!) of computing time (remote, Colab Pro).

The best performing single classifier (after five-fold cross-validation) is Ridge (L2) with an accuracy of 68.1%, using the tfidf-transformed dfm. It requires ~9 seconds of computing time (locally).

Our supervised text classification works better for some issue areas and worse for others.

The size of the training dataset affects the accuracy of our model. Our analysis suggests that an enlargement of our training dataset would only lead to marginal performance improvements. On the contrary, the Transformers model already yields an accuracy of over 70% with only about 750 coded press releases.

2 Setting up

This script requires the files which are not included on GitHub.

2.1 Loading packages

This script is based mainly on the functions of the quanteda package. For the cross-validation of the textmodels, quanteda.classifiers has to be loaded from GitHub.

```r
start_time <- Sys.time()

packages <- c("quanteda", "quanteda.textmodels", "dplyr", "caret", "randomForest",
    "tm", "rmarkdown", "plyr", "readr", "ggplot2", "stringr", "formatR", "readstata13",
    "lubridate", "reticulate", "doMC", "glmnet", "kableExtra", "stargazer", "extrafont",
    "tidyr", "ggrepel")

lapply(packages[!(packages %in% rownames(installed.packages()))], install.packages)

if (!("quanteda.classifiers" %in% rownames(installed.packages()))) {
    remotes::install_github("quanteda/quanteda.classifiers")
}

invisible(lapply(c(packages, "quanteda.classifiers"), require, character.only = T))

loadfonts()
loadfonts(device = "pdf")
theme_update(text = element_text(family = "LM Roman 10"))  # Set font family for ggplot

if (!dir.exists("supervised-files")) dir.create("supervised-files")

source("scripts/functions.R")
```

2.2 Loading document frequency matrix (dfm)

See other script for the generation of the dfm.

```r
load("supervised-files/data/dfmat.RData")
load("supervised-files/data/dfmat_alt.RData")

# Category descriptions
issue_categories <- data.frame(issue = c(1:10, 12:18, 20, 23, 98, 99, 191:192), issue_descr = c("Macroe
    "Civil Rights", "Health", "Agriculture", "Labor", "Education", "Environment",
    "Energy", "Immigration", "Transportation", "Law and Crime", "Social Welfare",
    "Housing", "Domestic Commerce", "Defense", "Technology", "Foreign Trade", "Government Operations",
    "Culture", "Non-thematic", "Other", "International Affairs", "European Integration"))


# Distribution with merged categories
table(dfmat$issue) %>%
    as.data.frame() %>%
    dplyr::rename(issue = Var1, n = Freq) %>%
    t() %>%
    kbl(booktabs = T) %>%
    kable_styling(latex_options = "scale_down")
```

issue	1	2	3	4	5	6	7	8	9	10	12	13	14	15	16	17	18	20	23	98	99	191	192
n	169	175	119	99	166	134	82	103	123	70	188	100	31	164	121	65	27	88	19	64	25	342	138

3 Textmodels

Following Barberá et al. (2021) we estimated the following models:

1. Naive Bayes (multinomial)
2. Ridge regression (L2)
3. Lasso regression (L1)
4. Elastic Net
5. SVM
6. Random Forest

(Barberá, P., Boydstun, A., Linn, S., McMahon, R., & Nagler, J. (2021). Automated Text Classification of News Articles: A Practical Guide. Political Analysis, 29(1), 19-42. doi:10.1017/pan.2020.8)

Additionally, we run the following models:

7. Superlearner (ensemble of single classifiers)
8. Semi-supervised (Elastic net)
9. Transformers model (BERT)

Finally, we also test the performance of Readme2 for the estimation of proportions. (An evaluation of the classification of individual documents is not possible for this method.)

The individual models are run in previous scripts.

An overview of the results for each classifier can be found in this script.

4 Aggregating the results of the classifiers

```r
# Create a dataframe for all textmodels and save first row
tm_eval <- data.frame()

# 1 Naive bayes
load("supervised-files/textmodels/naivebayes_eval.RData")
(naivebayes_eval_aggr <- aggregate(cbind(accuracy, precision, recall, f1_score, time,
    seed) ~ weight + distribution + smooth + model, naivebayes_eval[, -c(1)], mean) %>%
    arrange(desc(accuracy)))[1:5, ] %>%
    mutate_at(vars(accuracy, precision, recall, f1_score), function(x) round(x, 3)) %>%
    kbl(booktabs = T)
```

weight	distribution	smooth	model	accuracy	precision	recall	f1_score	time	seed
tfidf	multinomial	1	Naive bayes	0.666	0.686	0.602	0.608	0.220	1621447882
uniform	multinomial	1	Naive bayes	0.640	0.613	0.599	0.590	0.200	1621447882
docfreq	multinomial	1	Naive bayes	0.637	0.614	0.589	0.585	0.158	1621447882
termfreq	multinomial	1	Naive bayes	0.637	0.612	0.590	0.583	0.154	1621447882
uniform	multinomial	2	Naive bayes	0.612	0.648	0.529	0.535	0.150	1621447882

```r
naivebayes_eval_aggr$time <- naivebayes_eval_aggr$time/60
tm_eval <- naivebayes_eval_aggr %>%
    rbind.fill(tm_eval)

# 2 Ridge regression (L2)
```

```r
load("supervised-files/textmodels/ridge_eval.RData")
(ridge_eval_aggr <- aggregate(cbind(accuracy, precision, recall, f1_score, time,
    seed) ~ weight + type + model, ridge_eval[, -c(1)], mean) %>%
    arrange(desc(accuracy)))[1:5, ] %>%
    mutate_at(vars(accuracy, precision, recall, f1_score), function(x) round(x, 3)) %>%
    kbl(booktabs = T)
```

	weight	type	model	accuracy	precision	recall	f1_score	time	seed
1	tfidf	7	Ridge (L2)	0.669	0.677	0.609	0.624	3.9275	1621447882
2	tfidf	0	Ridge (L2)	0.666	0.678	0.605	0.621	4.9225	1621447882
3	uniform	0	Ridge (L2)	0.596	0.591	0.543	0.553	1.1740	1621447882
4	uniform	7	Ridge (L2)	0.594	0.588	0.541	0.551	2.2260	1621447882
NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

```r
ridge_eval_aggr$time <- ridge_eval_aggr$time/60
tm_eval <- ridge_eval_aggr %>%
    rbind.fill(tm_eval)

# 3 Lasso regression (L1)
load("supervised-files/textmodels/lasso_eval.RData")
(lasso_eval_aggr <- aggregate(cbind(accuracy, precision, recall, f1_score, time,
    seed) ~ weight + model, lasso_eval[, -c(1)], mean) %>%
    arrange(desc(accuracy)))[1:2, ] %>%
    mutate_at(vars(accuracy, precision, recall, f1_score), function(x) round(x, 3)) %>%
    kbl(booktabs = T)
```

weight	model	accuracy	precision	recall	f1_score	time	seed
tfidf	Lasso (L1)	0.605	0.611	0.560	0.568	5.880	1621447882
uniform	Lasso (L1)	0.576	0.559	0.528	0.531	1.136	1621447882

```r
lasso_eval_aggr$time <- lasso_eval_aggr$time/60
tm_eval <- lasso_eval_aggr %>%
    rbind.fill(tm_eval)

# 4 Elastic net
load("supervised-files/textmodels/elasticnet_opt_alt.RData")
load("supervised-files/textmodels/elasticnet_mod.RData")
load("supervised-files/textmodels/elasticnet_pred.RData")
elastic_net_test <- dfm_subset(dfmat, dfmat$cv_sample == 1)

# If alternative model is better:
if (elasticnet_opt_alt) {
    load("supervised-files/textmodels/elasticnet_mod_alt.RData")
    elasticnet_mod <- elasticnet_mod_alt
    load("supervised-files/textmodels/elasticnet_pred_alt.RData")
    elasticnet_pred <- elasticnet_pred_alt
    elastic_net_test <- dfm_subset(dfmat_alt, dfmat_alt$cv_sample == 1)
}


tm_eval <- data.frame(accuracy = accuracy(elasticnet_pred, elastic_net_test$issue),
    precision = precision(elasticnet_pred, elastic_net_test$issue) %>%
        unlist() %>%
        mean(), recall = recall(elasticnet_pred, elastic_net_test$issue) %>%
        unlist() %>%
        mean(), f1_score = f1_score(elasticnet_pred, elastic_net_test$issue) %>%
        unlist() %>%
        mean(), time = elasticnet_mod$time, seed = elasticnet_mod$seed, weight = elasticnet_mod$weight,
    model = elasticnet_mod$model, alpha = 0.5, distribution = "multinomial") %>%
    rbind.fill(tm_eval)

# 5 SVM
load("supervised-files/textmodels/svm_eval.RData")
(svm_eval_aggr <- aggregate(cbind(accuracy, precision, recall, f1_score, time, seed) ~
    weight + model, svm_eval[, -c(1)], mean) %>%
    arrange(desc(accuracy)))[1:3, ] %>%
    mutate_at(vars(accuracy, precision, recall, f1_score), function(x) round(x, 3)) %>%
    kbl(booktabs = T)
```

weight	model	accuracy	precision	recall	f1_score	time	seed
tfidf	SVM	0.653	0.652	0.608	0.616	3.396	1621447882
docfreq	SVM	0.569	0.564	0.529	0.534	0.552	1621447882
termfreq	SVM	0.567	0.558	0.520	0.527	0.650	1621447882

```
svm_eval_aggr$time <- svm_eval_aggr$time/60
tm_eval <- svm_eval_aggr %>%
    rbind.fill(tm_eval)

# 6 Random Forest
load("supervised-files/textmodels/randomforest_opt_alt.RData")
load("supervised-files/textmodels/randomforest_eval.RData")
load("supervised-files/textmodels/randomforest_pred.RData")
randomforest_test <- dfm_subset(dfmat, dfmat$cv_sample == 1)

# If alternative model is better:
if (randomforest_opt_alt) {
    load("supervised-files/textmodels/randomforest_eval_alt.RData")
    randomforest_mod <- randomforest_eval_alt
    load("supervised-files/textmodels/randomforest_pred_alt.RData")
    randomforest_pred <- randomforest_pred_alt
    randomforest_test <- dfm_subset(dfmat_alt, dfmat_alt$cv_sample == 1)
}

tm_eval <- data.frame(accuracy = accuracy(randomforest_pred, randomforest_test$issue),
    precision = precision(randomforest_pred, randomforest_test$issue) %>%
        unlist() %>%
        mean(na.rm = T), recall = recall(randomforest_pred, randomforest_test$issue) %>%
        unlist() %>%
        mean(na.rm = T), f1_score = f1_score(randomforest_pred, randomforest_test$issue) %>%
        unlist() %>%
        mean(na.rm = T), time = randomforest_eval$time, seed = randomforest_eval$seed,
    model = randomforest_eval$model, weight = randomforest_eval$weight, alpha = 0.5,
    distribution = "multinomial") %>%
    rbind.fill(tm_eval)
```

```r
# 7 SuperLearner Load superlearner prediction and add row to evaluation table
super_pred <- read_csv("superlearner-files/super-pred.csv", col_names = F)
```

```
## Rows: 2612 Columns: 3

## -- Column specification --------------------------------------------------------
## Delimiter: ","
## dbl (3): X1, X2, X3

##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
names(super_pred) <- c("prediction", "issue", "cv_sample")
supertime <- read_csv("superlearner-files/cv-time.txt", col_names = F, col_types = "n")[1,
    1] %>%
    as.numeric()
superlearner_test <- dfm_subset(dfmat_alt, dfmat$cv_sample == 1)$issue

tm_eval <- data.frame(accuracy = accuracy(super_pred$prediction, super_pred$issue),
    precision = precision(super_pred$prediction, super_pred$issue) %>%
        unlist() %>%
        mean(), recall = recall(super_pred$prediction, super_pred$issue) %>%
        unlist() %>%
        mean(), f1_score = f1_score(super_pred$prediction, super_pred$issue) %>%
        unlist() %>%
        mean(), time = supertime, weight = "tfidf", seed = 1621447882, model = "SuperLearner ensemble")
    rbind.fill(tm_eval)


# 8 Semi-supervised Load Semi-supervised prediction and add row to evaluation
# table
semi_pred <- read_csv("semi-files/semi-pred.csv", col_names = F)
```

```
## Rows: 2612 Columns: 3

## -- Column specification --------------------------------------------------------
## Delimiter: ","
## dbl (3): X1, X2, X3

##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
names(semi_pred) <- c("prediction", "issue", "cv_sample")
semitime <- read_csv("semi-files/cv-time.txt", col_names = F, col_types = "n") %>%
    as.numeric()/60

tm_eval <- data.frame(accuracy = accuracy(semi_pred$prediction, semi_pred$issue),
    precision = precision(semi_pred$prediction, semi_pred$issue) %>%
        unlist() %>%
        mean(), recall = recall(semi_pred$prediction, semi_pred$issue) %>%
        unlist() %>%
        mean(), f1_score = f1_score(semi_pred$prediction, semi_pred$issue) %>%
        unlist() %>%
        mean(), time = semitime, weight = "tfidf", seed = 1621447882, model = "Semi-supervised") %>%
    rbind.fill(tm_eval)
```

```r
# 9 Transformers Load transfer models prediction and add row to evaluation
# table
transfer_pred <- read_csv("transfer-files/bert-pred.csv", col_names = F)
```

```
## Rows: 2612 Columns: 4

## -- Column specification --------------------------------------------------------
## Delimiter: ","
## dbl (4): X1, X2, X3, X4

##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
names(transfer_pred) <- c("prediction", "issue", "label", "cv_sample")
transfertime <- read_csv("transfer-files/cv-time.txt", col_names = F, col_types = "n") %>%
    as.numeric()/60

tm_eval <- data.frame(accuracy = accuracy(transfer_pred$prediction, transfer_pred$label),
    precision = precision(transfer_pred$prediction, transfer_pred$label) %>%
        unlist() %>%
        mean(), recall = recall(transfer_pred$prediction, transfer_pred$label) %>%
        unlist() %>%
        mean(), f1_score = f1_score(transfer_pred$prediction, transfer_pred$label) %>%
        unlist() %>%
        mean(), time = transfertime, seed = 1621447882, model = "GBERT (Transformers)") %>%
    rbind.fill(tm_eval)

# Add var for instance type
tm_eval <- mutate(tm_eval, instance = ifelse(str_detect(model, "(GBER)|(Super)|(Semi)"),
    "remote", "local"))
```

```r
aggregate(accuracy ~ weight, tm_eval, mean)  # tfidf gives overall best performance
```

```
##     weight  accuracy
## 1  docfreq 0.6033666
## 2 termfreq 0.6018355
## 3    tfidf 0.6538699
## 4  uniform 0.5972638
```

The tfidf-transformed dfm yields a higher performance for most classifiers and parameter settings.

5 Evaluation of textmodels

In this section, we present a table for comparison of our textmodels. We compare the model with the highest accuracy for each classifier.

```r
# Only keep best model for each classifier
tm_eval <- tm_eval %>%
    dplyr::group_by(model) %>%
    dplyr::mutate(acc_rank = order(order(accuracy, decreasing = TRUE))) %>%
    filter(acc_rank == 1) %>%
    select(-c(acc_rank))

# Comparison of textmodels
```

```
tm_eval[, c("accuracy", "precision", "recall", "f1_score", "time")] <- apply(tm_eval[,
    c("accuracy", "precision", "recall", "f1_score", "time")], MARGIN = 2, function(x) round(x,
    3))

tm_eval[order(tm_eval$accuracy, decreasing = T), c("model", "weight", "accuracy",
    "precision", "recall", "f1_score", "time")] %>%
    kbl(booktabs = T, row.names = F)
```

model	weight	accuracy	precision	recall	f1_score	time
GBERT (Transformers)	NA	0.764	0.760	0.754	0.756	9.207
SuperLearner ensemble	tfidf	0.680	0.687	0.619	0.640	12547.280
Ridge (L2)	tfidf	0.669	0.677	0.609	0.624	0.065
Naive bayes	tfidf	0.666	0.686	0.602	0.608	0.004
SVM	tfidf	0.653	0.652	0.608	0.616	0.057
Semi-supervised	tfidf	0.637	0.716	0.543	0.585	0.602
Elastic net	uniform	0.609	0.621	0.571	0.583	8.290
Lasso (L1)	tfidf	0.605	0.611	0.560	0.568	0.098
Random forest	uniform	0.589	0.676	0.519	0.550	5.434

```
latex_out <- capture.output(tm_eval[order(tm_eval$accuracy, decreasing = T), c("model",
    "weight", "accuracy", "precision", "recall", "f1_score", "time")] %>%
    dplyr::rename(Model = model, DFM = weight, Accuracy = accuracy, Precision = precision,
        Recall = recall, `F1 score` = f1_score, `Time (min)` = time) %>%
    stargazer(out = "tables/tm-eval.tex", summary = F, rownames = F, title = "Summary of classifier per
        label = "tab:tm-eval"))
```

We obtain the highest accuracy of 77.5% using the pretrained Transformers model GBERT fine-tuned with our labeled dataset. It requires ~8 minutes of computing time (remote, Colab Pro).

The Superlearner ensemble of single supervised classifiers obtains 71.2% accuracy, using the tfidf-transformed dfm. It requires ~18 minutes of computing time (remote, Colab Pro).

The best performing single classifier (after five-fold cross-validation) is Ridge (L2) with an accuracy of 68.1%, using the tfidf-transformed dfm. It requires ~9 seconds of computing time (locally).

The Naive bayes classifier obtains 67.0% accuracy in only 0.23 seconds (locally).

In the following, we therefore use this model to evaluate the performance of the supervised text classification.

6 Confusion matrix

Since some issue areas might be more suitable for an supervised classification than others, we analyze the accuracy for individual issues and present a confusion matrix.

To do so, we rely on the top-performing single classifier, Ridge (L2), as well as the fine-tuned Transformers model.

6.1 Ridge (L2)

```
# Baseline model (highest cross-validated accuracy)
ridge_pred <- data.frame()
for (i in 1:5) {
    print(i)
    ridge_pred <- data.frame(prediction = textmodel_svm(dfm_subset(dfmat_alt, dfmat_alt$cv_sample !=
        i), dfm_subset(dfmat_alt, dfmat_alt$cv_sample != i)$issue, type = 7) %>%
        predict(., newdata = dfm_subset(dfmat_alt, dfmat_alt$cv_sample == i)), issue = dfm_subset(dfmat_
        dfmat_alt$cv_sample == i)$issue) %>%
        rbind.fill(ridge_pred)
}
```

```
## [1] 1

## Warning: 3 features in newdata not used in prediction.

## [1] 2

## Warning: 2 features in newdata not used in prediction.

## [1] 3
## [1] 4

## Warning: 1 feature in newdata not used in prediction.

## [1] 5

## Warning: 2 features in newdata not used in prediction.
```

```
# Confusion matrix and overall statistics
ridge_pred$issue %>%
    table
```

```
## .
##   1   2   3   4   5   6   7   8   9  10  12  13  14  15  16  17  18  20  23  98
## 169 175 119  99 166 134  82 103 123  70 188 100  31 164 121  65  27  88  19  64
##  99 191 192
##  25 342 138
```

```
truth <- ridge_pred$issue
truth[truth == 191] <- 19.1
truth[truth == 192] <- 19.2
truth <- factor(truth, levels = c(1:10, 12:18, 19.1, 19.2, 20, 23, 98, 99))

prediction <- ridge_pred$prediction
prediction[prediction == 191] <- 19.1
prediction[prediction == 192] <- 19.2
prediction <- factor(prediction, levels = c(1:10, 12:18, 19.1, 19.2, 20, 23, 98,
    99))

ridge_pred <- data.frame(truth, prediction, model = "Ridge (L2)")

(table(prediction, truth) %>%
    confusionMatrix(mode = "sens_spec", dnn = c("predicted", "truth")))$table
```

```
##             truth
## prediction   1   2   3   4   5   6   7   8   9  10  12  13  14  15  16  17  18
##        1   115   1   0   0  11   2   3   2   1   3   4   3   1   8   0   2   1
##        2     0  96  12   1   5   2   3   0   5   0  15   6   0   5   3   4   0
##        3     0   7  90   1   4   0   0   0   0   0   4   2   0   1   0   0   0
##        4     0   1   5  80   0   0   8   0   0   0   0   0   1   6   0   0   0
##        5    20   0   1   0 127   1   0   0   3   2   1  11   0   2   0   1   0
##        6     2   4   1   0   1 110   0   0   4   0   1   7   0   3   0   4   0
##        7     2   0   1   1   0   1  25   6   0   3   1   0   0   1   0   1   0
##        8     1   0   0   0   0   0  10  77   0   2   0   0   3   1   0   2   0
##       9      1   3   0   0   4   0   0   0  93   0   6   1   1   1   0   0   0
##       10     0   0   0   1   1   0   3   2   0  39   1   0   0   3   0   1   0
##       12     2  27   5   0   2   1   0   3   5   6 127   0   0   8   7   2   0
##       13     1   6   1   0   2   8   0   0   0   0   0  61   1   1   0   0   0
##       14     0   0   0   0   0   0   0   3   0   0   0   0  18   0   0   0   0
##       15     8   3   1  12   3   1   7   4   2   4   8   2   3  87   0  13   0
##       16     0   3   0   0   0   0   1   0   0   0   6   0   0   3  69   1   1
##       17     2   1   0   1   0   1   0   1   0   2   3   0   0   3   0  28   0
##       18     0   0   0   0   0   0   0   0   0   0   1   0   0   0   0   0  17
##       19.1   5  17   2   1   3   1  17   3   7   4   5   3   1  10  36   2   5
##       19.2   5   0   0   1   2   0   2   0   1   1   2   0   0  13   3   0   1
##       20     3   5   0   0   0   1   3   2   1   4   2   3   2   4   3   1   1
##       23     0   0   0   0   1   3   0   0   0   0   0   0   0   0   0   3   1
##       98     2   1   0   0   0   2   0   0   0   0   0   1   0   3   0   0   0
##       99     0   0   0   0   0   0   0   0   1   0   1   0   0   1   0   0   0
##           truth
## prediction 19.1 19.2  20  23  98  99
##       1       1    4  11   1   3   2
##       2       9    1  10   0   2   3
##       3       0    0   0   0   1   0
##       4       1    0   0   0   0   0
##       5       0    1   1   2   3   0
##       6       0    0   2   1   1   1
##       7       9    0   0   0   0   0
##       8       0    0   0   0   0   0
##       9       1    3   1   0   0   1
##       10      0    2   3   0   0   0
##       12      4    2  11   2   3   1
##       13      0    0   0   0   0   0
##       14      0    0   1   0   0   0
##       15      7   11   2   3   0   0
##       16     14    0   4   0   2   0
##       17      0    0   1   3   2   0
##       18      1    0   0   0   0   0
##       19.1  281   28   4   1   8   0
##       19.2    8   82   2   0   1   1
##       20      1    1  33   1   4   0
##       23      0    1   0   5   1   0
##       98      4    1   2   0  33   0
##       99      1    1   0   0   0  16
```

```r
latex_out <- capture.output(as.data.frame(unclass((table(prediction, truth) %>%
    confusionMatrix(mode = "sens_spec", dnn = c("predicted", "truth")))$table)) %>%
    stargazer(summary = F, title = "Confusion matrix for the test data (Ridge L2)",
        label = "tab:confusion-mat-ridge"))

latex_out <- capture.output(latex_out %>%
    str_replace_all("tabular", "tabularx") %>%
    str_replace_all("\\@\\{\\\\extracolsep\\{5pt\\}\\} ccccccccccccccccccc", "\\\\textwidth\\}\\{XXXXXXX
    cat(sep = "\n"), file = "tables/confusion-mat-ridge.tex")

issue_eval_ridge <- data.frame(truth = truth, prediction = prediction) %>%
    group_by(truth) %>%
    dplyr::mutate(accuracy = accuracy(truth, prediction)) %>%
    select(-c("prediction")) %>%
    unique() %>%
    merge(., data.frame(truth = levels(truth), precision = precision(truth, prediction),
        recall = recall(truth, prediction), f1_score = f1_score(truth, prediction)),
        by = "truth") %>%
    dplyr::rename(Accuracy = accuracy, Precision = precision, Recall = recall, `F1 score` = f1,
        Issue = truth)
issue_eval_ridge[, c("Accuracy", "Precision", "Recall", "F1 score")] <- issue_eval_ridge[,
    c("Accuracy", "Precision", "Recall", "F1 score")] %>%
    apply(., MARGIN = 2, FUN = function(x) round(as.numeric(x), 3))

# Change and order labels
issue_eval_ridge$Issue <- factor(issue_eval_ridge$Issue, levels = c(1:10, 12:18,
    19.1, 19.2, 20, 23, 98, 99))

issue_eval_ridge <- issue_eval_ridge[order(issue_eval_ridge$Issue), ]
issue_eval_ridge$Issue <- str_c(as.character(issue_eval_ridge$Issue), " - ", issue_categories[c(1,
    10, 11:17, 22:23, 2, 18:19, 3:9, 20:21), 2])

# Accuracy
accuracy(truth, prediction)
```

```
## $accuracy
## [1] 0.6542879
```

6.2 Transformers (GBERT)

```
# Import results
transfer_pred <- read_csv("transfer-files/bert-pred.csv", col_names = F)
```

```
## Rows: 2612 Columns: 4
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## dbl (4): X1, X2, X3, X4
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
names(transfer_pred) <- c("prediction_label", "issue", "label", "cv_sample")
labels <- select(transfer_pred, c(label, issue)) %>%
    unique %>%
    dplyr::rename(prediction = issue)
transfer_pred <- merge(transfer_pred, labels, by.x = "prediction_label", by.y = "label") %>%
    select(-c(prediction_label))

# Confusion matrix and overall statistics
transfer_pred$issue %>%
    table
```

```
## .
##   1   2   3   4   5   6   7   8   9  10  12  13  14  15  16  17  18  20  23  98
## 169 175 119  99 166 134  82 103 123  70 188 100  31 164 121  65  27  88  19  64
##  99 191 192
##  25 342 138
```

```r
truth <- transfer_pred$issue
truth[truth == 191] <- 19.1
truth[truth == 192] <- 19.2
truth <- factor(truth, levels = c(1:10, 12:18, 19.1, 19.2, 20, 23, 98, 99))

prediction <- transfer_pred$prediction
prediction[prediction == 191] <- 19.1
prediction[prediction == 192] <- 19.2
prediction <- factor(prediction, levels = c(1:10, 12:18, 19.1, 19.2, 20, 23, 98,
    99))

transfer_pred <- data.frame(truth, prediction, model = "Transformers")

(table(prediction, truth) %>%
    confusionMatrix(mode = "sens_spec", dnn = c("predicted", "truth")))$table
```

```
##           truth
## prediction   1   2   3   4   5   6   7   8   9  10  12  13  14  15  16  17  18
##       1    126   0   1   0   5   1   1   0   0   0   2   2   0  10   0   1   0
##       2      0 112   4   0   3   3   0   0   3   0  18   5   1   3   1   1   0
##       3      3   3 100   4   2   0   0   0   0   0   1   1   0   0   0   0   0
##       4      0   0   5  90   0   0   2   0   0   0   0   0   0   4   0   0   0
##       5     10   0   1   0 139   4   0   0   2   1   0  11   1   1   0   0   0
##       6      0   3   1   0   2 109   0   0   4   0   0   6   0   1   0   3   0
##       7      1   0   1   2   0   0  64   5   0   6   0   0   0   1   0   0   0
##       8      2   0   0   0   0   0   7  94   0   0   0   0   2   1   0   1   0
##       9      0   5   0   0   0   0   0   0 109   0   6   0   0   0   1   0   0
##       10     0   0   0   0   2   0   3   1   0  59   2   0   0   5   0   0   0
##       12     0  19   3   0   1   0   0   0   1   1 138   1   0   5   2   0   0
##       13     1   6   1   0   7   8   0   0   0   0   1  70   0   1   0   0   0
##       14     0   0   0   0   0   0   0   1   0   0   0   0  25   0   0   0   0
##       15     7   2   0   1   1   1   1   1   0   2   5   1   1 113   0   5   0
##       16     0   1   0   0   0   1   0   0   1   0   7   1   0   2 101   0   0
##       17     4   2   0   0   1   2   0   0   0   0   0   0   0   3   0  48   0
##       18     2   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0  22
##       19.1   1  11   2   2   2   0   4   1   1   0   3   0   0   4  12   1   5
##       19.2   4   1   0   0   1   0   0   0   1   0   1   0   0   7   1   1   0
##       20     5   5   0   0   0   0   0   0   0   1   4   1   1   2   3   1   0
##       23     0   0   0   0   0   4   0   0   0   0   0   0   0   1   0   3   0
##       98     3   4   0   0   0   1   0   0   0   0   0   1   0   0   0   0   0
##       99     0   0   0   0   0   0   0   0   1   0   0   0   0   0   0   0   0
##           truth
## prediction 19.1 19.2   20   23   98   99
##       1       3    3    6    0    0    1
##       2      12    0    5    1    2    0
##       3       2    0    0    0    1    0
##       4       2    0    0    0    0    0
##       5       0    0    1    1    1    0
##       6       0    0    0    1    1    1
##       7       9    0    0    0    0    0
##       8       0    0    1    0    0    0
##       9       1    3    1    0    0    0
##       10      0    2    6    0    0    0
##       12      4    1   10    0    1    2
##       13      0    0   2   0   1   0
##       14      0    0   1   0   1   0
##       15      6   10   4   3   0   0
##       16     17    1   5   0   1   0
##       17      0    1   0   3   0   0
##       18      2    0   0   0   0   0
##       19.1  271   16   1   0   4   0
##       19.2    8   98   1   0   1   1
##       20      1    2  41   0   9   0
##       23      0    0   0   9   1   0
##       98      4    1   3   1  39   1
##       99      0    0   0   0   1  19
```

```
latex_out <- capture.output(as.data.frame(unclass((table(prediction, truth) %>%
    confusionMatrix(mode = "sens_spec", dnn = c("predicted", "truth")))$table)) %>%
    stargazer(summary = F, title = "Confusion matrix for the test data (Transformers)",
        label = "tab:confusion-mat-transfer"))

latex_out <- capture.output(latex_out %>%
    str_replace_all("tabular", "tabularx") %>%
    str_replace_all("\\@\\{\\\\extracolsep\\{5pt\\}\\} cccccccccccccccccc", "\\\\textwidth\\}\\{XXXXXXX
    cat(sep = "\n"), file = "tables/confusion-mat-transfer")

issue_eval_transfer <- data.frame(truth = truth, prediction = prediction) %>%
    group_by(truth) %>%
    dplyr::mutate(accuracy = accuracy(truth, prediction)) %>%
    select(-c("prediction")) %>%
    unique() %>%
    merge(., data.frame(truth = levels(truth), precision = precision(truth, prediction),
        recall = recall(truth, prediction), f1_score = f1_score(truth, prediction)),
        by = "truth") %>%
    dplyr::rename(Accuracy = accuracy, Precision = precision, Recall = recall, `F1 score` = f1,
        Issue = truth)

issue_eval_transfer[, c("Accuracy", "Precision", "Recall", "F1 score")] <- issue_eval_transfer[,
    c("Accuracy", "Precision", "Recall", "F1 score")] %>%
    apply(., MARGIN = 2, FUN = function(x) round(as.numeric(x), 3))

# Order and add names
issue_eval_transfer <- issue_eval_transfer[order(issue_eval_transfer$Issue), ]
issue_eval_transfer$Issue <- str_c(as.character(issue_eval_transfer$Issue), " - ",
    issue_categories[c(1, 10, 11:17, 22:23, 2, 18:19, 3:9, 20:21), 2])

# Write latex table
if (!dir.exists("tables")) dir.create("tables")

# Accuracy
accuracy(truth, prediction)
```

```
## $accuracy
## [1] 0.7641654
```

```
# Merge with issue_eval_ridge
issue_eval_ridge_transfer <- merge(select(issue_eval_ridge, c(Issue, Accuracy)) %>%
    dplyr::rename(Ridge = Accuracy), select(issue_eval_transfer, c(Issue, Accuracy)) %>%
    dplyr::rename(Transformers = Accuracy), by = "Issue")
issue_eval_ridge_transfer <- issue_eval_ridge_transfer[order(issue_eval_ridge_transfer$Issue %>%
    str_extract("^[:digit:]\\.?[:digit:]?") %>%
    as.numeric()), ]

latex_out <- capture.output(issue_eval_ridge_transfer %>%
    stargazer(out = "tables/issue-eval-ridge-transfer.tex", summary = F, rownames = F,
        title = "Performance statistics by issue for different models", label = "tab:issue_eval_transfe

accuracy(truth[!(truth %in% c(2, 20, 98, 99))], prediction[!(truth %in% c(2, 20,
    98, 99))])
```

```
## $accuracy
## [1] 0.789823
```

Regarding the issues, the classifiers works better for specific issue categories.

While some have a higher than average sensitivity (e.g. 4 - Agriculture, 7 - Env. & Energy, 9 - Immigration, 191 - Int. Affairs), others fare worse than average (e.g. 2- Civil Rights, 20 - Gov. Ops., 99 - Other). Unsurprisingly, these rather unspecific categories are difficult to predict. Without them, the accuracy of the Transformers model rises to above 80%.

The better sensitivity for other categories is likely the result of a more specific use of words. Category 17 - Technology may feature a worse accuracy (especially for Ridge) because it is underrepresented in the labeled data. Category 15 - Commerce is often misclassified as 191 - Int. Affairs and 192 - EU: Categories where a press release may contain similar words.

16 - Defense is often misclassified as 191 - International Affairs.

7 Accuracy of predicted proportions

Since we are most interested in the prediction of proportions (i.e. how many press releases were dedicated to issue X in a given time frame), we analyze the accuracy of predicted proportions.

To do so, we rely on the top-performing single classifier, Ridge (L2), and perform a five-fold cross-validation.

We find the greatest average difference in predicted and actual proportions for 19.1 - International Affairs with 4.8%. And the lowest for 6 - Education wit 0.4%.

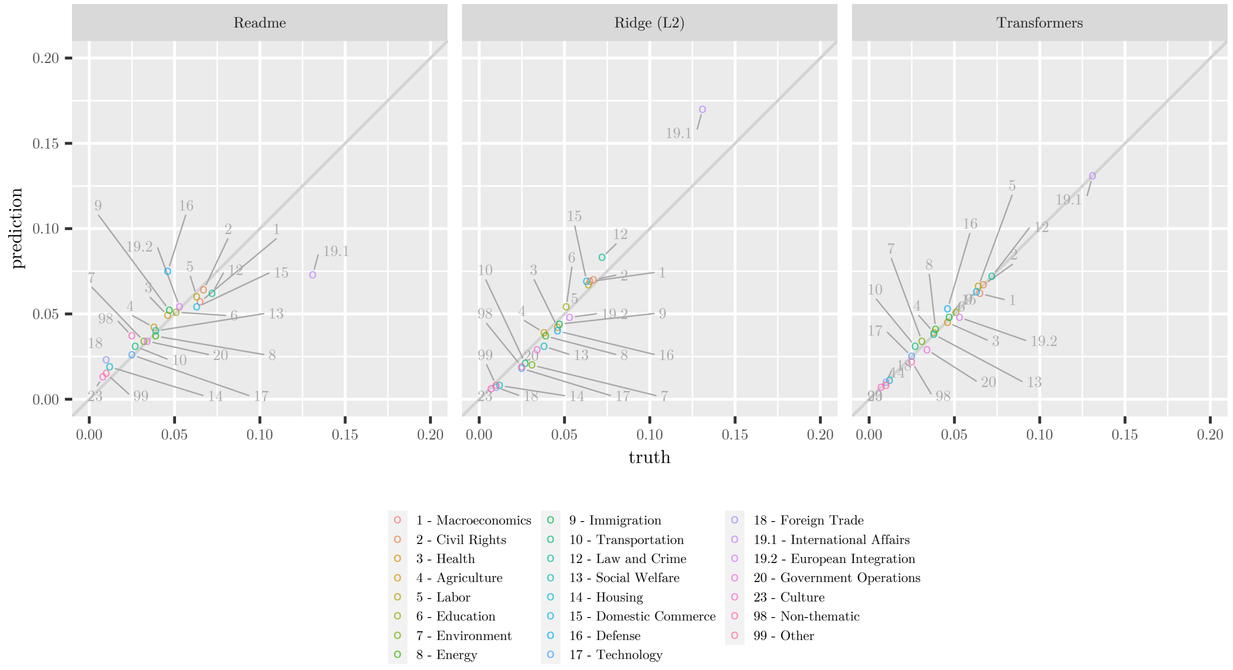
The MSE is 1.33%.

```
# Load
load("readme-files/agg_eval.RData")
readme_agg <- agg_eval

# Aggregate Accuracy of predicted proportions (five-fold cross-validation)

# Ridge
ridge_agg <- merge(table(ridge_pred$truth)/nrow(ridge_pred), table(ridge_pred$prediction)/nrow(ridge_pr
    by = "Var1") %>%
    dplyr::rename(Issue = Var1, truth = Freq.x, prediction = Freq.y) %>%
    dplyr::mutate(model = "Ridge (L2)")
ridge_agg <- ridge_agg[order(ridge_agg$Issue), ]
ridge_agg$Issue <- str_c(as.character(ridge_agg$Issue), " - ", issue_categories[c(1:17,
    22:23, 18:21), 2]) %>%
    factor()
```

```
# Transformers
transfer_agg <- merge(table(transfer_pred$truth)/nrow(transfer_pred), table(transfer_pred$prediction)/n
    by = "Var1") %>%
    dplyr::rename(Issue = Var1, truth = Freq.x, prediction = Freq.y) %>%
    dplyr::mutate(model = "Transformers")
transfer_agg <- transfer_agg[order(transfer_agg$Issue), ]
transfer_agg$Issue <- str_c(as.character(transfer_agg$Issue), " - ", issue_categories[c(1:17,
    22:23, 18:21), 2]) %>%
    factor()

# Readme
readme_agg <- readme_agg %>%
    dplyr::rename(Issue = issue, prediction = predicted) %>%
    select(-c(cv_sample, difference)) %>%
    dplyr::group_by(Issue) %>%
    dplyr::mutate(prediction = mean(prediction), truth = mean(truth), model = "Readme") %>%
    unique()

three_agg <- rbind.fill(readme_agg, transfer_agg, ridge_agg)

# Difference in percentage points (positive values indicate an inflated
# prediction, i.e. we estimate a higher share for the category compared to the
# truth)
three_agg$difference <- three_agg$prediction - three_agg$truth
three_agg[, c("truth", "prediction", "difference")] <- apply(three_agg[, c("truth",
    "prediction", "difference")], MARGIN = 2, function(x) round(x, 3))  # Round

# MSE
print(sum((three_agg$difference * 100)^2)/nrow(three_agg))  # 1.056
```

```
## [1] 1.055652
```

```
# Plot Plotting aggregate evaluation in one plot
ggplot(three_agg, aes(x = truth, y = prediction)) + geom_abline(slope = 1, color = "light grey") +
    geom_text_repel(label = three_agg$Issue %>%
        str_extract("[:digit:]{1,2}(\\.[:digit:])?"), box.padding = 0.4, color = "dark grey",
        size = 2, family = "LM Roman 10", segment.size = 0.25, min.segment.length = 0.1,
        point.padding = 0.15, max.overlaps = 100) + geom_point(shape = "o", aes(color = Issue),
    alpha = 0.75) + ylim(c(0, 0.2)) + xlim(c(0, 0.2)) + guides(color = guide_legend(ncol = 3)) +
    labs(color = "Issue category") + theme(legend.position = "bottom", legend.title = element_blank(),
    aspect.ratio = 1, text = element_text(size = 7), legend.key.size = unit(0.5,
        "line"), legend.text = element_text(size = 5)) + facet_wrap(~model)
```



```
ggsave("plots/agg_eval_compare_facet.pdf", device = cairo_pdf, width = 3 * 2^0.5,
    height = 3)

ggsave("plots/agg_eval_compare_facet.png", width = 3 * 2^0.5, height = 3)
```

```
## Warning in grid.Call(C_stringMetric, as.graphicsAnnot(x$label)): font family not
## found in Windows font database

## Warning in grid.Call(C_stringMetric, as.graphicsAnnot(x$label)): font family not
## found in Windows font database

## Warning in grid.Call(C_stringMetric, as.graphicsAnnot(x$label)): font family not
## found in Windows font database

## Warning in grid.Call(C_textBounds, as.graphicsAnnot(x$label), x$x, x$y, : font
## family not found in Windows font database

## Warning in grid.Call(C_textBounds, as.graphicsAnnot(x$label), x$x, x$y, : font
## family not found in Windows font database

## Warning in grid.Call(C_textBounds, as.graphicsAnnot(x$label), x$x, x$y, : font
## family not found in Windows font database

## Warning in grid.Call(C_textBounds, as.graphicsAnnot(x$label), x$x, x$y, : font
## family not found in Windows font database

## Warning in grid.Call.graphics(C_text, as.graphicsAnnot(x$label), x$x, x$y, :
## font family not found in Windows font database
## Warning in grid.Call(C_textBounds, as.graphicsAnnot(x$label), x$x, x$y, : font
## family not found in Windows font database

## Warning in grid.Call.graphics(C_text, as.graphicsAnnot(x$label), x$x, x$y, :
## font family not found in Windows font database

## Warning in grid.Call(C_textBounds, as.graphicsAnnot(x$label), x$x, x$y, : font
## family not found in Windows font database
```

```r
# Write table
three_agg <- three_agg %>%
    select(c(Issue, difference, model)) %>%
    pivot_wider(id_cols = "Issue", names_from = "model", values_from = "difference")

three_agg %>%
    kbl(booktabs = T, row.names = F)
```

Issue	Readme	Transformers	Ridge (L2)
1 - Macroeconomics	-0.007	-0.003	0.004
2 - Civil Rights	-0.003	0.000	0.003
3 - Health	0.003	-0.001	-0.003
4 - Agriculture	0.004	0.002	0.001
5 - Labor	-0.004	0.003	0.004
6 - Education	0.000	-0.001	0.003
7 - Environment	0.002	0.003	-0.012
8 - Energy	-0.003	0.002	-0.003
9 - Immigration	0.004	0.001	-0.003
10 - Transportation	0.004	0.004	-0.005
12 - Law and Crime	-0.010	0.000	0.011
13 - Social Welfare	0.001	-0.001	-0.007
14 - Housing	0.007	-0.001	-0.003
15 - Domestic Commerce	-0.009	0.000	0.007
16 - Defense	0.029	0.007	-0.007
17 - Technology	0.001	0.000	-0.007
18 - Foreign Trade	0.012	0.000	-0.003
20 - Government Operations	0.001	-0.005	-0.005
23 - Culture	0.005	0.000	-0.002
98 - Non-thematic	0.012	-0.002	-0.006
99 - Other	0.005	-0.002	-0.002
19.1 - International Affairs	-0.058	0.000	0.039
19.2 - European Integration	0.002	-0.005	-0.005

```r
latex_out <- capture.output(three_agg %>%
    stargazer(out = "tables/aggregated-eval.tex", summary = F, rownames = F, title = "Difference betwee
        label = "tab:aggregated-eval"))
```

8 Key features for the categories

```r
# Ridge (L2) with full labeled data
tm_ridge <- textmodel_svm(dfmat_alt, dfmat_alt$issue, type = 7)

# Key words/features for classified topics
```

```
key_feats <- data.frame()
for (i in rownames(tm_ridge$weights)) key_feats <- data.frame(issue = i) %>%
    cbind(sort(tm_ridge$weights[which(rownames(tm_ridge$weights) == i), ], decreasing = T)[1:5] %>%
        attr("names") %>%
        str_replace_all("\\_", " ") %>%
        t) %>%
    rbind.fill(key_feats)

key_feats <- key_feats[order(key_feats$issue %>%
    str_replace_all(c(`191` = "19.1", `192` = "19.2")) %>%
    as.numeric), ]

key_feats$issue <- levels(readme_agg$issue)
```

```
## Warning: Unknown or uninitialised column: `issue`.
```

```
key_feats %>%
    kbl(booktabs = T, row.names = F)
```

1	2	3	4	5
investitionen	haushalt	steuern	einnahmen	vermögen
frauen	pegida	menschen mit	datenschutz	gleichstellung
pflege	patienten	prävention	versicherten	rösler
landwirtschaft	tierschutz	aigner	glyphosat	agrarpolitik
mindestlohn	rent	beschäftigten	beschäftigt	beschäftigung
hochschulen	bildung	schulen	bafö	studierenden
klimaschutz	lärm	ressourcen	klimapolitik	umwelt
energiewend	gorleben	energien	energiekonzept	atomausstieg
flüchtling	integr	zuwanderung	migranten	nach deutschland
verkehrspolitisch	verkehr	autofahr	straßen	dobrindt
verfassungsschutz	straftaten	vorratsdatenspeicherung	kriminalität	täter
betreuungsgeld	elterngeld	hartz	kindergeld	familien
wohnraum	städtebauförderung	stadtentwicklung	städte	mieter
bank	tourismus	banken	finanztransaktionssteu	verbrauch
bundeswehr	waffen	nato	soldaten	rüstungsexport
digital	digitalisierung	internet	sender	rundfunk
ttip	ceta	abkommen	freihandelsabkommen	freihandel
russland	iran	israel	wahlen	menschenrecht
ezb	griechenland	ungarn	mitgliedstaaten	zypern
wowereit	kommunen	steinbach	öffentlichkeit	berlin
kultur	kulturgüt	kultur und	und medien	\ "
tod	bundesvorstand	wahl	trauern	teilt mit
frage :	. frage	kauder	liberal	jenseit

```
latex_out <- capture.output(stargazer(key_feats, summary = F, title = "Key features for each issue (Rid
    label = "tab:key_feats", out = "tables/key_feats.tex"))
```

9 Training data size and accuracy

To test the influence of the size of the training dataset on the accuracy, we estimate models with smaller sizes.

To do so, we rely on the top-performing single classifier, Ridge (L2), as well as the fine-tuned Transformers model.

The size of the training dataset affects the accuracy of our model. Our analysis suggests that an enlargement of our training dataset would only lead to marginal performance improvements. On the contrary, the Transformers model already yields an accuracy of over 70% with only about 750 coded press releases.

```
trainsize_ridge <- c(5, 25, 50, 100, 200, 300, 400, 500, 600, 700, 1000, 1500, 1750,
    2000, 2095)
trainsize_ridge <- data.frame(Model = "Ridge (L2)", train_size = trainsize_ridge)

trainsize_ridge$accuracy <- sapply(trainsize_ridge$train_size, FUN = function(x) {
    sub_train <- sample(1:ndoc(dfm_subset(dfmat_alt, dfmat_alt$cv_sample != 5)),
        x)
    ridge_opt_mod <- textmodel_svm(dfm_subset(dfmat_alt, dfmat_alt$cv_sample != 5)[sub_train,
        ], dfm_subset(dfmat_alt, dfmat_alt$cv_sample != 5)$issue[sub_train], type = 7)
    accuracy(dfm_subset(dfmat_alt, dfmat_alt$cv_sample == 5)$issue, predict(ridge_opt_mod,
        newdata = dfm_subset(dfmat_alt, dfmat_alt$cv_sample == 5)))
}) %>%
    unlist

# Load the results from GBERT transformer models
trainsize_transfer <- read_csv("transfer-files/results-training-size.csv", col_names = F)
names(trainsize_transfer) <- c("accuracy", "train_size")
trainsize_transfer$Model <- "GBERT"
train_size <- rbind(trainsize_transfer, trainsize_ridge)

# Load the results from multilingual transformer models
trainsize_multi <- read_csv("other-countries/results-training-size.csv", col_names = F)
names(trainsize_multi) <- c("accuracy", "train_size")
trainsize_multi$Model <- "Multi-lingual"
train_size <- rbind(train_size, trainsize_multi)

ggplot(train_size, aes(x = train_size, y = accuracy)) + theme(text = element_text(size = 16)) +
    # geom_smooth(aes(color = Model, lty = Model), method = 'loess', formula =
    # 'y ~ x', se = F) +
geom_line(aes(group = Model, color = Model, lty = Model), stat = "smooth", method = "loess",
    formula = "y ~ x", size = 0.7, linetype = 2, alpha = 0.7, se = F) + geom_point(aes(color = Model,
    shape = Model)) + xlab("Size of training dataset") + ylab("Accuracy")
ggsave(str_c("plots/training-size-simulation.pdf"), device = cairo_pdf, width = 5 *
    2^0.5, height = 5)
ggsave(str_c("plots/training-size-simulation.png"), width = 5 * 2^0.5, height = 5)
```

```
# Time needed to run script (much shorter when textmodels are just loaded from
# a file) The estimation time for the single textmodels can found in the table
# above.

print(Sys.time() - start_time)
```

```
## Time difference of 29.62844 secs
```

```
# In total, the script needs about 2-3h to run.
```