Computational Sociology

Supervised Text Classification

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Plan

1. Course updates
2. Introduction to supervised text classification
3. Supervised text classification in R
4. Data sampling and annotation

Course updates

Homework

- Homework 3 due today at 8pm
  - Submit using Github

Course updates

Projects

- Project Prototype next Friday, 11/19 at 5pm
  - Live app on shinyapps.io
  - Link to code on Github
    - Add my username if using a private repository
- Presentations 12/6 & 12/8
- Finished app 12/16

Introduction to supervised text classification

What is it?

- Supervised text classification involves using machine-learning to automatically label documents
  - Phase 1: Select a corpus of documents
  - Phase 2: Annotate a small sample of documents with "ground truth" labels
  - Phase 3: Train a model to predict the labels of the annotated documents
  - Phase 4: Use the trained model to predict the labels for the entire corpus
- We generally use this in cases where it is impractical to categorize all documents by hands

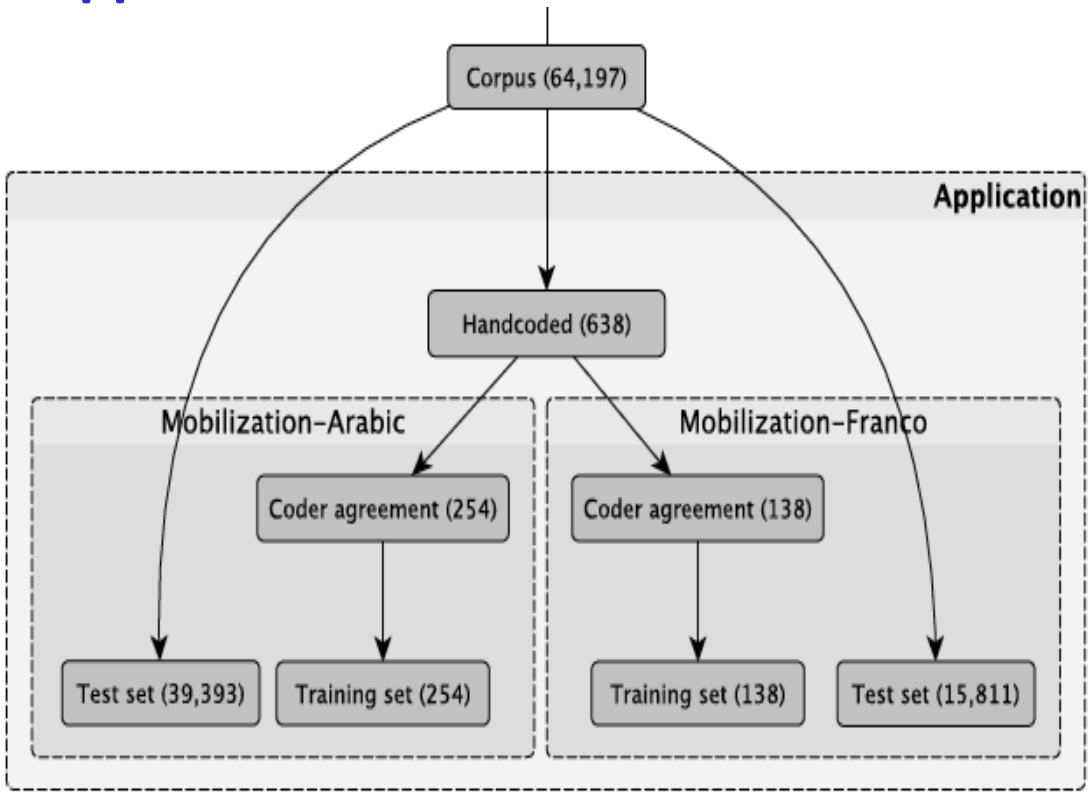
Introduction to supervised text classification

Supervised versus unsupervised approaches

- Both supervised text classification and topic modeling can be used as a replacement for conventional content analysis
  - Topic modeling is an *inductive* approach, useful for summarizing an entire corpus and deriving categories
  - Supervised machine learning is a *deductive* approach, designed to classify documents into discrete (or probabilistic) classes based on pre-defined categoriess
    - Unlike topic modeling, the categories are known in advance to the analyst

Introduction to supervised text classification

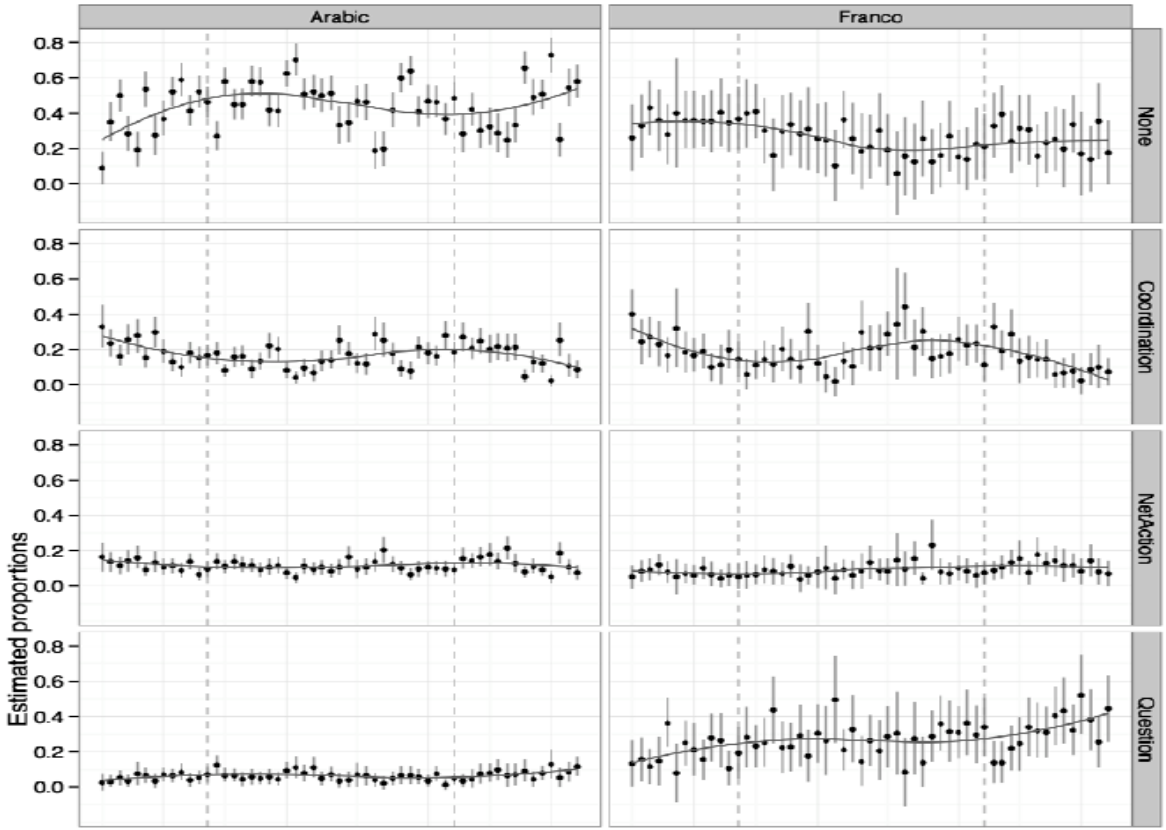
Sociological applications



Hanna, Alex. 2013.

Introduction to supervised text classification

Sociological applications



Supervised text classification in R

Case study

- Data
  - A subsample of the IMBD reviews dataset*
    - 5000 IMBD reviews
    - half positive ($\geq 7/10$), half negative ($\leq 4/10$), neutral excluded.
- Classification task
  - Predict which reviews are positive and which are negative (binary)
- All code is based on examples from Emil Hvitfeldt and Julia Silge, *Supervised Machine Learning for Text Analysis in R*, *forthcoming*, Chapter 7.

Maas, Andrew L, Raymond E Daly, Peter T Pham, Dan Huang, Andrew Y Ng, and Christopher Potts. 2011. "Learning Word Vectors for Sentiment Analysis." In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics*, 142–50.

Supervised text classification in R

Loading data

In this case, we take a random sample of the training data to make the process more tractable. I have commented out the sampling code and provided the sampled dataset.

```
library(tidyverse)
path <- 'data/imbd_reviews_sample.tsv'
d <- read_tsv(path)

d %>% filter(sentiment == "pos") %>% count()
```

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Train-test split

The first step is to divide our dataset into training and testing data.

```
library(tidymodels)
set.seed(8954)

review_split <- initial_split(d, strata="sentiment", prop = 0.8)
train <- training(review_split)
test <- testing(review_split)
```

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Creating a `recipe`

We begin by creating a `recipe` by specifying the equation and the dataset.

```
review_recipe <- recipe(sentiment ~ text, data  = train)
```

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Adding preprocessing steps

Next, we can use the `textrecipes` library to add preprocessing steps to our recipe. Note that we could also do our preferred preprocessing first using `tidytext` or another package then pass the resulting data directly to our recipe.

```
library(textrecipes)
review_recipe <- review_recipe %>% step_tokenize(text) %>%
  step_tokenfilter(text, max_tokens = 1000) %>%
  step_tfidf(text)
```

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Creating a `workflow`

Once we have a recipe, we're going to be using something called a `workflow` to chain together a sequence of modeling operations.

```
review_wf <- workflow() %>% add_recipe(review_recipe)
```

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Adding a model

We can then add more operations to our workflow to train a model. In this case we will use a logistic regression with a LASSO penalty.

```
# install.packages("glmnet")
lasso <- logistic_reg(penalty = 0.01, mixture = 1) %>%
  set_mode("classification") %>%
  set_engine("glmnet")

review_wf <- review_wf %>% add_model(lasso)
```

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Reviewing the `workflow`

We can print the workflow to review the sequence of operations to be performed.

```
print(review_wf)
```

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Cross-validation

We can then incorporate cross-validation into our model to get a better estimate of out-of-sample performance. In this case we use k-fold/v-fold cross-validation, where k/v is set to 10.

```
review_folds <- vfold_cv(train, v = 10)
```

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Fitting a cross-validated model

We can then use the `fit_resamples` function from the `tune` package to fit our workflow to each of the 10 subsets of data. The `control` parameter specifies information we want to store for further analysis.

```
fitted <- fit_resamples(
  review_wf,
  review_folds,
  control = control_resamples(save_pred = TRUE),
  metrics = metric_set(precision, recall, f_meas, roc_auc)
)
```

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Evaluating overall performance

The `collect_` functions from the `tune` package then allow us to evaluate each model.

```
lasso_pred_probs <- collect_predictions(fitted, type = "prob")

collect_metrics(fitted)
```

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Evaluating performance by fold

By grouping on `id` we can view the estimate for each cross-validation sub-group.

```
lasso_pred_probs %>% group_by(id) %>%
  f_meas(sentiment, .pred_class) %>%
  select(id, .estimate)
```

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Computing an ROC curve

We can view the performance of each classifier using the ROC curve. In general they all appear to perform quite well.

```
library(viridis)
lasso_pred_probs %>%
  group_by(id) %>%
  roc_curve(truth = sentiment, .pred_neg) %>%
  autoplot() +
  labs(
    color = NULL,
    title = "ROC curve for IMBD review sentiment predictions",
    y = "True positive rate",
    x = "False positive rate"
  ) + scale_color_viridis_d(option="magma")
```

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Selecting tuning parameters

Now we have code we can use to fit a model using cross-validation. The next step is to find the optimal set of parameters. In this case there are two things we might want to vary: the size of the feature matrix and the regularization strength. To do this we need to modify the recipe and model object to specify that we want to tune these parameters.

```
review_recipe_2 <- recipe(sentiment ~ text, data  = train) %>% step_tok
  step_tokenfilter(text, max_tokens = tune()) %>%
  step_tfidf(text)

review_wf <- review_wf %>% update_recipe(review_recipe_2)

lasso_2 <- logistic_reg(penalty = tune(), mixture = 1) %>%
  set_mode("classification") %>%
  set_engine("glmnet")

review_wf <- review_wf %>% update_model(lasso_2)
```

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Specifying a parameter grid

Next, we specify a parameter grid using `grid_regular` this defines the parameter space and how it should be broken down. We specify a range of values for each parameter and how many cut-points in this range we are interested in.

```
param_grid <- grid_regular(
  penalty(range = c(-4, 0)),
  max_tokens(range = c(1000, 5000)),
  levels = c(penalty = 5, max_tokens = 5)
)

print(param_grid)
```

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Fitting the model to the parameter grid

Finally, we use `tune_grid` to fit the workflow to these different tuning parameters, using the same cross-validation splits as above. This will take a while since we have 5x5x10 model fits accounting for the combinations of tuning parameters and number of folds. This is similar in logic to the `fit_resamples` but it returns the model with the best-fitting parameters.

```
tune_params <- tune_grid(
  review_wf,
  review_folds,
  grid = param_grid,
  metrics = metric_set(precision, recall, f_meas, roc_auc),
  control = control_resamples(save_pred = TRUE)
)
```

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Evaluating performance by parameter

Let's take a look at the results. We have 100 observations (5 x 5 x 4 metrics).

```
tuned_metrics <- collect_metrics(tune_params)

tuned_metrics %>% group_by(penalty, .metric) %>%
  summarize(mean_score= mean(mean)) %>%
  filter(.metric == "f_meas")

tuned_metrics %>% group_by(max_tokens, .metric) %>%
  summarize(mean_score= mean(mean)) %>%
  filter(.metric == "f_meas")
```

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Plotting the results

Even better, we can directly plot the relationship between the variables. In this case it seems like the regularization makes a much bigger difference than the size of the feature matrix.

```
autoplot(tune_params) +
  labs(title = "Lasso model performance across regularization penalties
       color = "Number of tokens") + scale_color_viridis_d()
```

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Selecting the best model and updating the workflow

Let's take the model with the best F1 score and fit it to our data.

```
best_f1 <- tune_params %>% select_best(metric = "f_meas")
print(best_f1)

final_wf <- finalize_workflow(review_wf, best_f1)

print(final_wf)
```

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Fitting the model to the training data

Now we can fit the model to our entire training dataset *and* assess its performance on the test set, which has not been used so far. Note how we are not using cross-validation now, we are re-training the best model using all of the training data.

```
final_fitted <- last_fit(final_wf, review_split)
```

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Evaluating out-of-sample performance

```
collect_metrics(final_fitted)
```

Supervised text classification in R

Evaluating out-of-sample performance

```
final.precision <- collect_predictions(final_fitted) %>% precision(truth
final.recall <- collect_predictions(final_fitted) %>% recall(truth=sent
final.f1 <- collect_predictions(final_fitted) %>% f_meas(truth=sentimen
print(bind_rows(final.precision, final.recall, final.f1))
```

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Evaluating out-of-sample performance

```
collect_predictions(final_fitted) %>%
  conf_mat(truth = sentiment, estimate = .pred_class) %>%
  autoplot(type = "heatmap") #+ scale_fill_viridis_c()
```

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Evaluating out-of-sample performance

We can similarly view the ROC curve for the held-out data. This shows that our model performs well out-of-sample.

```
collect_predictions(final_fitted, type="prob")  %>%
  roc_curve(truth = sentiment, estimate = .pred_neg) %>%
  autoplot() +
  labs(
  color = NULL,
  title = "ROC curve for IMBD review sentiment predictions",
  y = "True positive rate",
  x = "False positive rate"
  ) + scale_color_viridis_d(option="magma")
```

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Error analysis

The final step we can take is to conduct some analysis of the predictions. In particular, its often most insightful to look at the errors.

```
reviews_bind <- collect_predictions(final_fitted) %>%
  bind_cols(test %>% select(-sentiment))

pos_errors <- reviews_bind %>%
  filter(sentiment == "pos", .pred_pos < 0.3) %>%
  select(text) %>%
  slice_sample(n = 5) %>% print()

neg_errors <- reviews_bind %>%
  filter(sentiment == "neg", .pred_neg < 0.3) %>%
  select(text) %>%
  slice_sample(n = 5) %>% print()
```

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Calculating feature importance

We can also find out which features are most important to gain some insight into how the model is working. The `vip` package allows us to calculate feature importance scores and to see which are most strongly associated with each class.

```
library(vip)

reviews_imp <- pull_workflow_fit(final_fitted$.workflow[[1]]) %>%
  vi(lambda = best_f1$penalty)

imp <- reviews_imp %>%
  mutate(
    Sign = case_when(Sign == "POS" ~ "More positive",
                     Sign == "NEG" ~ "More negative"),
    Importance = abs(Importance),
    Variable = str_remove_all(Variable, "tfidf_text_"),
  ) %>%
  group_by(Sign) %>%
```

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Visualizing feature importance

```
imp %>%
  ggplot(aes(x = Importance,
             y = fct_reorder(Variable, Importance),
             fill = Sign)) +
  geom_col(show.legend = FALSE) +
  scale_x_continuous(expand = c(0, 0)) +
  facet_wrap(~Sign, scales = "free") +
  labs(
    y = NULL,
    title = "Feature importance for predicting the valence of an IMBD r
  ) + scale_fill_viridis_d(option="plasma")
```

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Next steps

- We only considered a single model. In a real-world application it would be worth repeating these steps for a variety of different classifiers, including parameter tuning.
  - SVM and neural networks both work well for text classification problems
- We also only tested a single type of feature (TF-IDF weighted unigrams)
  - Consider other representations
    - N-grams
    - LSA
    - Document embeddings (Word2vec, GLoVE, BERT)
  - Evaluate the impact of different pre-processing techniques
  - Additional non-textual features if available

Summary

- Supervised text classification combines NLP and ML to classify documents into classes
- In contrast with topic modeling, it is a deductive approach
- Training data must be carefully sampled and annotated
- Model features and parameters are selected to maximize predictive accuracy
- Error analysis and feature importance provide insight into model performance and limitations
- Once a model performs well and has been validated out-of-sample, we use it to predict the remainder of the corpus