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 2 (APIs and web-scraping) comments have been released
  - Please contact me if I have not given feedback HW1 or HW2
- Homework 3 (NLP) was due today at 4pm
- Homework 4 (Machine learning) will be released at the end of next week
  - Tentative due date is 4/22

Course updates

Project timeline

- Initial data collection
  - Deadline extended until 4/13 (next Monday) at 4pm
  - Submission instructions will be sent via Slack
- Preliminary analyses
  - Due 4/30 at 5pm

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

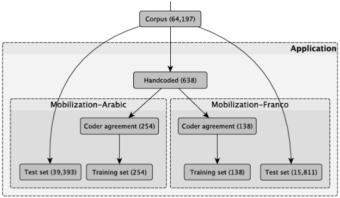
Introduction to supervised text classification

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

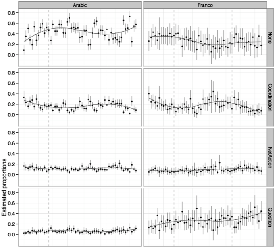
Sociological applications



Hanna, Alex. 2013.

Introduction to supervised text classification

Sociological applications



Introduction to supervised text classification

Sociological applications

- Laura Nelson (2017) proposes an approach called *computational grounded theory*
  - Start with an unsupervised approach to inductively summarize a corpus
  - Identify patterns and return to close reading of a corpus
  - Use supervised learning (and appropriate statistical texts) to confirm identified patterns
    - *Note: Assigned article does not actually used supervised machine learning but instead compares documents according to dictionary measures*

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)
  - The assumption that the classifier learns the sentiment of the reviews
- 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)
#library(textdata)
#d <- dataset_imdb(split="train")
#d.sample <- d %>% sample_n(5000)
path <- '../data/imbd_reviews_sample.tsv'
#write_tsv(d.sample, file=path)
d <- read_tsv(path)
d %>% filter(sentiment == "pos") %>% count()
```

```
## # A tibble: 1 x 1
##       n
##   <int>
## 1  2476
```

Supervised text classification in R

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)
```

Supervised text classification in R

Creating a `recipe`

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

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

Supervised text classification in R

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)
```

Supervised text classification in R

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)
```

Supervised text classification in R

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.

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

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

Supervised text classification in R

Reviewing the `workflow`

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

```
print(review_wf)
```

```
## == Workflow ==================================================
## Preprocessor: Recipe
## Model: logistic_reg()
##
## -- Preprocessor ----------------------------------------------
## 3 Recipe Steps
##
## * step_tokenize()
## * step_tokenfilter()
## * step_tfidf()
##
## -- Model -----------------------------------------------------
## Logistic Regression Model Specification (classification)
##
```

Supervised text classification in R

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)
)
```

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)
```

```
## # A tibble: 4 x 6
##   .metric   .estimator  mean     n std_err .config
##   <chr>     <chr>      <dbl> <int>   <dbl> <chr>
## 1 f_meas    binary     0.830    10 0.00548 Preprocessor1_Model1
## 2 precision binary     0.851    10 0.0113  Preprocessor1_Model1
## 3 recall    binary     0.812    10 0.0106  Preprocessor1_Model1
## 4 roc_auc   binary     0.907    10 0.00684 Preprocessor1_Model1
```

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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)
```

```
## # A tibble: 10 x 2
##    id     .estimate
##    <chr>      <dbl>
##  1 Fold01     0.834
##  2 Fold02     0.811
##  3 Fold03     0.828
##  4 Fold04     0.811
##  5 Fold05     0.822
##  6 Fold06     0.813
##  7 Fold07     0.861
##  8 Fold08     0.855
##  9 Fold09     0.833
```

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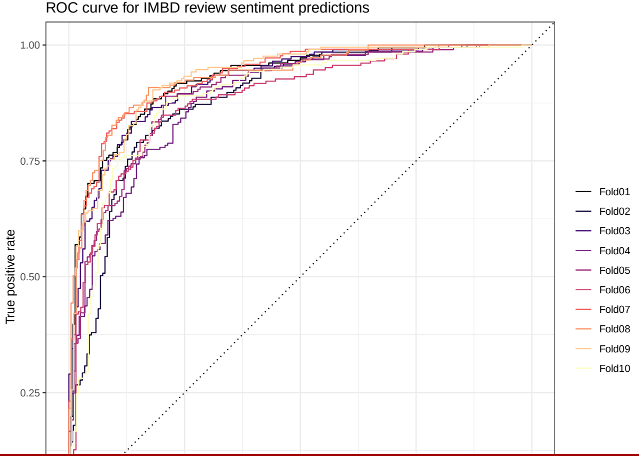
Computing an ROC curve

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



Supervised text classification in R

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)
```

Supervised text classification in R

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)
```

```
## # A tibble: 25 x 2
##    penalty max_tokens
##      <dbl>      <int>
##  1  0.0001       1000
##  2  0.001        1000
##  3  0.01         1000
```

Supervised text classification in R

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")
```

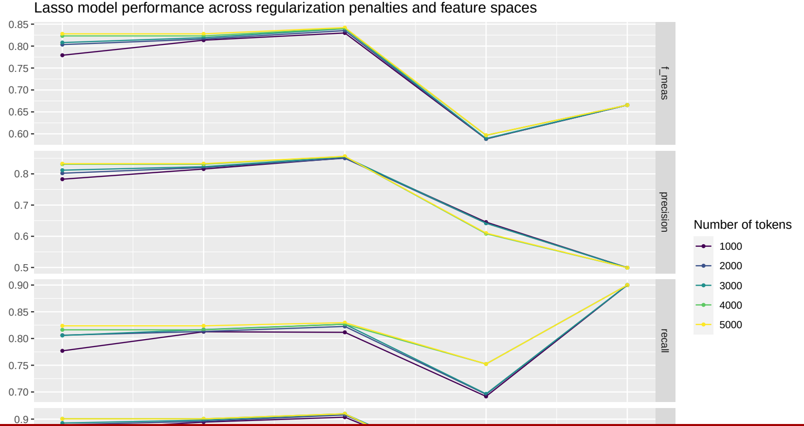
```
## # A tibble: 5 x 3
## # Groups:   penalty [5]
##   penalty .metric mean_score
##     <dbl> <chr>        <dbl>
## 1  0.0001 f_meas       0.808
## 2  0.001  f_meas       0.820
## 3  0.01   f_meas       0.837
## 4  0.1    f_meas       0.592
## 5  1      f_meas       0.666
```

```
tuned_metrics %>% group_by(max_tokens, .metric) %>%
```

Supervised text classification in R

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.



Supervised text classification in R

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)
```

```
## # A tibble: 1 x 3
##   penalty max_tokens .config
##     <dbl>      <int> <chr>
## 1    0.01       5000 Preprocessor5_Model3
```

```
final_wf <- finalize_workflow(review_wf, best_f1)

print(final_wf)
```

```
## == Workflow ==================================================
## Preprocessor: Recipe
## Model: logistic_reg()
##
## -- Preprocessor ----------------------------------------------
## 3 Recipe Steps
```

Supervised text classification in R

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)
```

Supervised text classification in R

Evaluating out-of-sample performance

```
collect_metrics(final_fitted)
```

```
## # A tibble: 2 x 4
##   .metric  .estimator .estimate .config
##   <chr>    <chr>          <dbl> <chr>
## 1 accuracy binary         0.859 Preprocessor1_Model1
## 2 roc_auc  binary         0.932 Preprocessor1_Model1
```

Supervised text classification in R

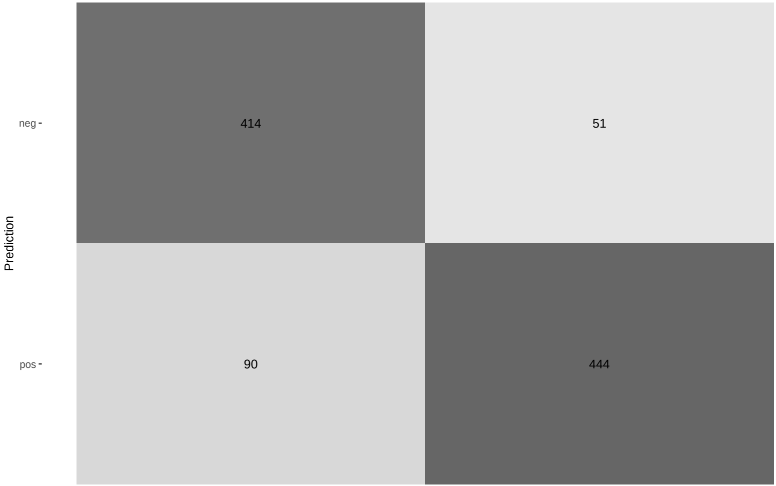
Evaluating out-of-sample performance

```
final.precision <- collect_predictions(final_fitted) %>% precision(trut
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))
```

```
## # A tibble: 3 x 3
##   .metric   .estimator .estimate
##   <chr>     <chr>          <dbl>
## 1 precision binary         0.890
## 2 recall    binary         0.821
## 3 f_meas    binary         0.854
```

Supervised text classification in R

Evaluating out-of-sample performance

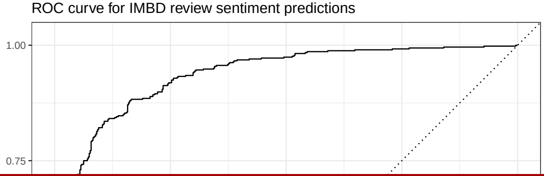


Supervised text classification in R

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")
```



Supervised text classification in R

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()
```

```
## # A tibble: 5 x 1
##   text
##   <chr>
## 1 "This show has all the typical characters in a comedy: the good gu
## 2 "There are moments in the film that are so dreadful, your teeth ac
## 3 "I think this movie got a low rating because it got judged by it's
## 4 "I really like this show. That is why I was disappointed to learn
```

Supervised text classification in R

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.

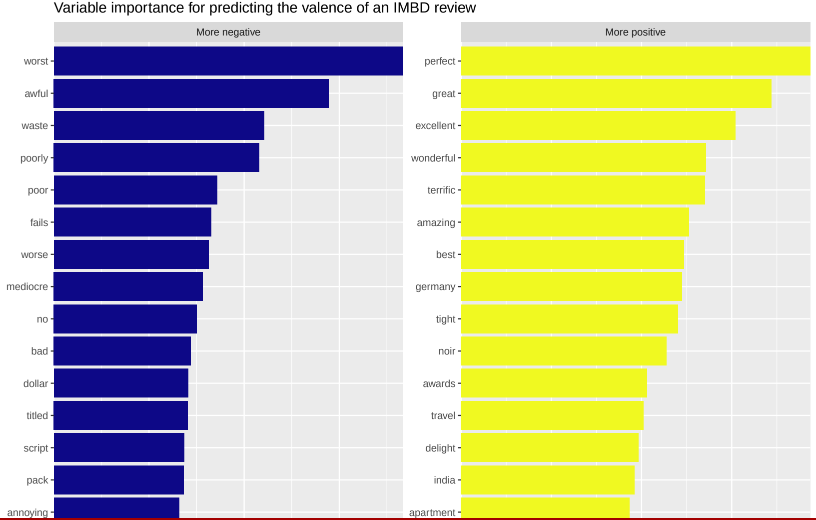
```
library(vip)

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) %>%
  top_n(15, Importance) %>%
```

Supervised text classification in R

Visualizing feature importance



Data sampling and annotation

Overview

- The previous example used a dataset with "ground truth" labels, derived from the numeric scores given to movies by IMDB users.
- In practice, we often have to produce this annotated dataset before we can train a model. This involves several decisions including:
  - What data do we want to classify and into what categories?
  - Which specific examples should we annotated?
  - How many cases do we need?
  - How should the annotation be conducted?

Data sampling and annotation

What data and categories?

- The choice of data and categories is usually driven by a combination of substantive and theoretical concerns.
- Consider the following example based on my research. The research focuses on political discourse about Brexit.
  - Sampling frame: Comments written on set of political pages on Facebook.
  - Categories: Is the comment relevant to the topic? If so, what is the stance of the comment?
    - Relevance is defined as binary (Relevant / Not relevant), although coders were also given a "Not sure" option.
    - Stance is defined as ternary (Pro-Leave / Pro-Remain / Neither), since we know from the public opinion literature that people do not always express views that have a clear stance. I also gave a "Not sure" option.

Data sampling and annotation

What data and categories?

- Important to consider *generalizability*
  - How well will the model perform on other datasets?
- Factors that might impact generalizability:
  - Context (e.g. publication, platform)
  - Time
  - Language / dialect
  - Medium (e.g. text, image, video)

Data sampling and annotation

The unit of analysis

- Select an appropriate unit of analysis
  - A book, a chapter, a paragraph, a sentence?
- This is usually guided by theory
  - e.g. If we want to classify the political leaning of a tweet then the unit is the tweet but if we want to classify users then we might consider aggregating their tweets.
- Barberá et al. 2020 find limited benefits to classifying sentences rather than chunks of newspaper articles, but this may not generalize to other cases

Data sampling and annotation

Keywords and categories

- In my case I used the context as a sampling frame, but we often have to select data based on the presence of keywords
  - e.g. Tweets containing particular hashtags
  - e.g. Newspaper articles containing keywords
- Sometimes we might find existing categorizations we can use to sample
  - e.g. the Twitter Academic API provides category labels for Tweets (e.g. politics, sports) based on Twitter's internal system
  - But Barberá et al. 2020 show how keywords are generally preferable to using proprietary

Data sampling and annotation

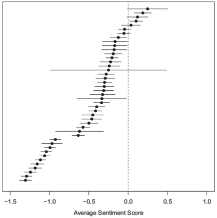
Keywords and categories

A Obamacare

King, Gary, Patrick Lam, and Margaret E. Roberts. 2017. "Computer-Assisted Keyword and Document Set Discovery from Unstructured Text." American Journal of Political Science 61 (4): 971–88.

Data sampling and annotation

Keywords and categories



Note: Each document set was selected by a different keyword list, with point estimates (as dots) and 95% confidence intervals (horizontal lines) shown.

Data sampling and annotation

Keywords and categories

- Recommendations
  - Start with a small set of keywords
  - Use an automated discovery approach* and/or domain expertise to expand the keyword set
  - Increase the size of the keyword set as long as returned documents increase but relevant proportion does not decline Barberá et al. 2020: 8).

Python code to implement King, Lam, and Roberts' approach.

Data sampling and annotation

Which specific examples should be annotated?

- Once we have our sample we need a way to select examples for annotation
  - The goal is to annotate a representative sample of documents such that we can train a classifier that generalizes well beyond the training data
- Generally we use some form of random sampling or stratified random sampling
  - For example, I began by sampling comments from Facebook pages, where the fraction from each page was proportional to the overall fraction of comments written on the page

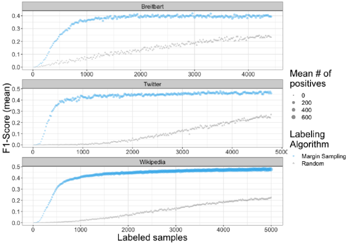
Data sampling and annotation

Which specific examples should be annotated?

- However, random sampling can be inefficient
  - Duplicate or highly similar documents are redundant
  - Many documents do not provide any new information
- We can do better by using an approach called *active learning*

Data sampling and annotation

Active learning in practice



Miller, Blake, Fridolin Linder, and Walter R. Mebane, Jr. 2019. "Active Learning Approaches for Labeling Text: Review and Assessment of the Performance of Active Learning Approaches." *Political Analysis*.

Data sampling and annotation

How many cases do we need?

- It depends a lot on the problem
  - How balanced are the class distributions?
    - e.g. Evenly split like IMBD or are some classes rare?
  - How difficult is the classification task?
- Barberá et al. 2020 show evidence of diminishing returns in a newspaper content classification task after ~1000 examples
- Mebane et al. 2019 demonstrate how active learning can reduce the necessary sample size compared to random sampling

Data sampling and annotation

How should annotation be conducted?

- Who should do the coding?
  - Expert coders vs. undergrads vs. crowdworkers
- How many coders per data point?
  - Barberá et al. 2020 find that it is preferable to have more examples coded by fewer people than fewer examples coded by more people
    - Although there should be some overlap for calculating intercoder-reliability

Data sampling and annotation

Final thoughts

- Data sampling and annotation is an overlooked area of research but has a huge impact on downstream applications
  - *Garbage in, garbage out*
- There are many different decisions involved that require careful consideration
  - Unlike the machine learning phase, we typically don't have the budget to do a grid-search over the parameter space!

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