# MY360/459 Quantitative Text Analysis: Machine Learning for Text

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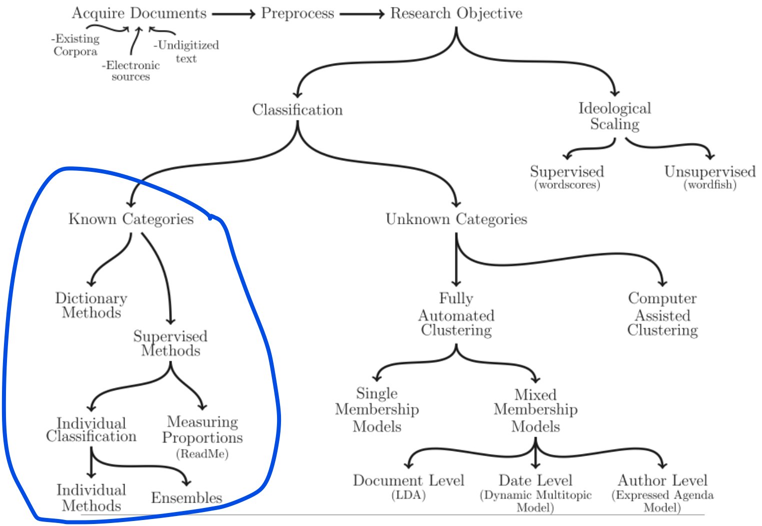
Slide content courtesy of Dr Blake Miller

February 5, 2024

Course website: lse-my459.github.io

1. Overview and Fundamentals
2. Descriptive Statistical Methods for Text Analysis
3. Automated Dictionary Methods
4. Machine Learning for Texts
5. Supervised Scaling Models for Texts
6. *Reading Week*
7. Unsupervised Models for Scaling Texts
8. Similarity and Clustering Methods
9. Topic models
10. Word embeddings
11. Working with Social Media

# Overview of text as data methods



# Outline

- Supervised learning overview
- Creating a labeled set and evaluating its reliability
- Classifier performance metrics
- Examples of classifiers
  - Naive Bayes
  - Regularized regression
- Active learning for labeling texts
- Applications of classifiers in social science research

# Supervised machine learning

**Goal**: classify documents into pre existing categories.

e.g. authors of documents, sentiment of tweets, ideological position of parties based on manifestos, tone of movie reviews...

**What we need**:

- Hand-coded dataset (labeled), to be split into:
  - Training set: used to train the classifier
  - Validation/Test set: used to validate the classifier
- Method to extrapolate from hand coding to unlabeled documents (classifier):
  - Naive Bayes, regularized regression, SVM, CNN, ensemble methods, etc.
- Approach to validate classifier: cross-validation
- Performance metric to choose best classifier and avoid overfitting: confusion matrix, accuracy, precision, recall...

# Supervised Learning

- $X$: data matrix, each column is called a feature, idependent variable, input variable (these can be words, n-grams, characters, word embeddings, etc.)
- $Y$: dependent variable/target
- Objective: Approximate the function of relationship between X and Y, make sure this function generalizes well to new data.
- Regression: $Y$ is a number
  - Linear regression is a very specialized case of regression
  - There are non-linear regression algorithms such as tree regression
- Classification: $Y$ is a value in an unordered set (i.e. $y_i \in \{\text{ordinary}, \text{bot}, \text{troll}, \text{cyborg}\}$)
- Training data: Pairs $(x_1, y_1), \ldots, (x_N, y_N)$ used to "train" a model that will later predict $y$ when given unseen test cases.
  - What are important/informative features?
  - How good are the model's predictions?/How useful is the model?

# The Process of Supervised Learning For Text Data

1. Gather documents
2. Preprocess documents
3. Describe the documents
4. Transform the documents (to a dfm)
5. Specify a model
6. Train the model
7. Evaluate model performance

# Classification v. scaling methods compared

- Machine learning focuses on identifying classes (classification), while social science is typically interested in locating things on latent traits (scaling)
- But the two methods overlap and can be adapted – will demonstrate later using the Naive Bayes classifier
- Applying lessons from machine learning to supervised scaling, we can
  - Apply classification methods to scaling
  - Improve it using lessons from machine learning

# Supervised v. unsupervised methods compared

- The goal (in text analysis) is to differentiate *documents* from one another, treating them as "bags of words"
- Different approaches:
  - *Supervised methods* for classification require a training set that exemplifies contrasting classes, identified by the researcher
  - *Unsupervised methods* identify similarities in documents based on patterns in the term-document matrix, without requiring supervision (human annotations)
- Relative advantage of supervised methods:

  You already know the dimension being scaled, because you set it in the training stage
- Relative disadvantage of supervised methods:

  You *must* already know the dimension being scaled, because you have to feed it good sample documents in the training stage

# Supervised v. unsupervised methods: Examples

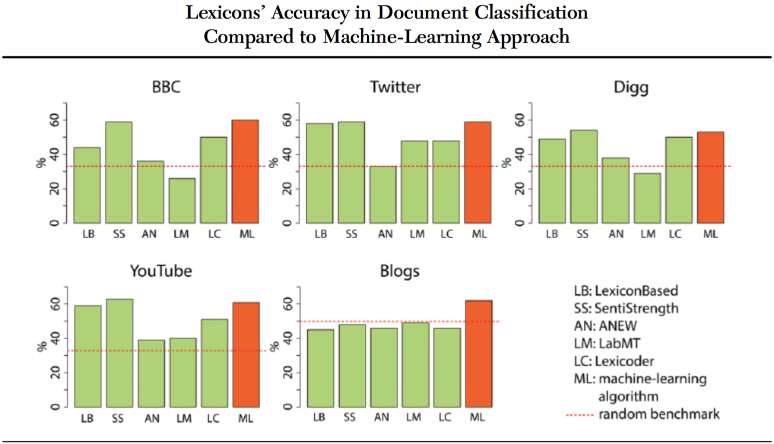
- General examples:
  - Supervised: Naive Bayes, regularized regression, support vector machines (SVM), convolutional neural networks (CNN)
  - Unsupervised: topic models, IRT models, correspondence analysis, factor analytic approaches
- Social science applications
  - Supervised: Wordscores (LBG 2003); SVMs (Yu, Kaufman and Diermeier 2008); Naive Bayes (Evans et al 2007)
  - Unsupervised: Structural topic model (Roberts et al 2014); "Wordfish" (Slapin and Proksch 2008); two-dimensional IRT (Monroe and Maeda 2004)

# Supervised learning v. dictionary methods

- Dictionary methods:
  - Advantage: not corpus-specific, cost to apply to a new corpus is trivial
  - Disadvantage: not corpus-specific, so performance on a new corpus is unknown (domain shift)
- Supervised learning can be conceptualized as a generalization of dictionary methods, where features associated with each categories (and their relative weight) are learned from the data
- By construction, they will outperform dictionary methods in classification tasks, as long as training sample is large enough

why???

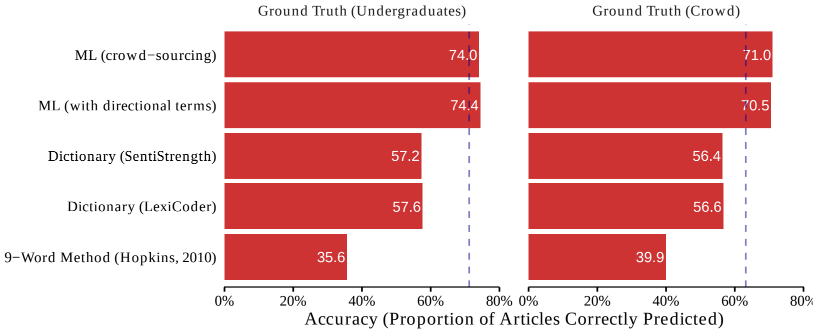
# Dictionaries vs supervised learning




**Source**: González-Bailón and Paltoglou (2015)

# Dictionaries vs supervised learning

Application: sentiment analysis of NYTimes articles




**Source**: Barberá et al (2017)

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# Creating a labeled set

How do we obtain a **labeled set**?

- External sources of annotation
  - Disputed authorship of Federalist papers estimated based on known authors of other documents
  - Party labels for election manifestos
  - Legislative proposals by think tanks (text reuse)
- Expert annotation
  - "Canonical" dataset in Comparative Manifesto Project
  - In most projects, undergraduate students (expertise comes from training)
- Crowd-sourced coding
  - **Wisdom of crowds**: aggregated judgments of non-experts converge to judgments of experts at much lower cost (Benoit et al, 2016)
  - Easy to implement with CrowdFlower or MTurk

# Code the Content of a Sample of Tweets

Instructions ▴

In this job, you will be presented with tweets about the recent protests related to race and law enforcement in the U.S.

You will have to read the tweet and answer a set of questions about its content.

Read the tweet below paying close attention to detail:

Tweet ID: **447**

**El Cid**
@JohnGalt2112

Follow

#BlackLivesMatter don't matter unless they are taken by a white cop.

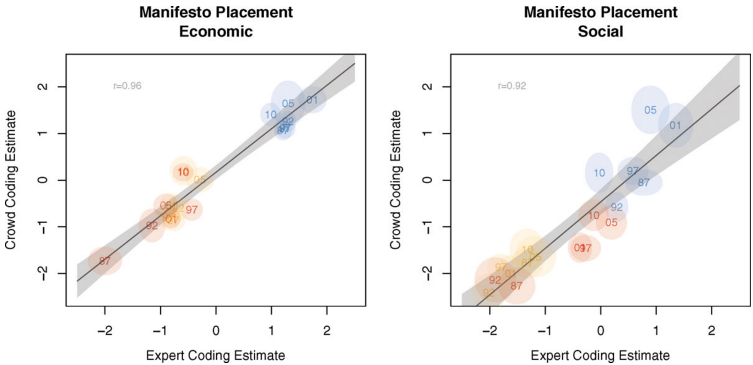
4:23 PM - 13 Dec 2014

**Is this tweet related to the ongoing debate about law enforcement and race in the United States?**

- ◯ Yes
- ◯ No
- ◯ Don't Know

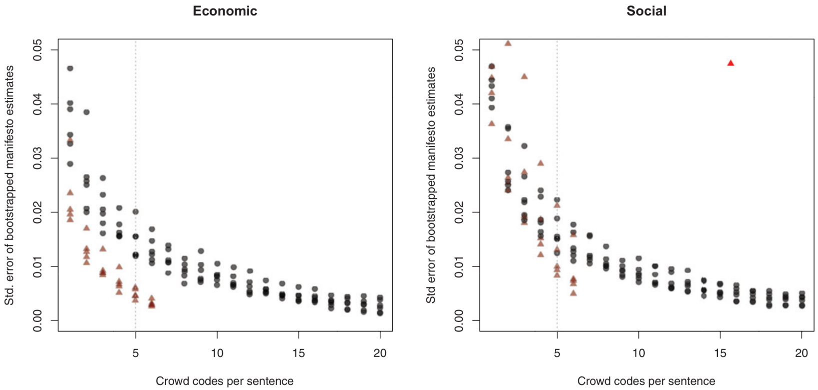
# Crowd-sourced text analysis (Benoit et al, 2016 APSR)

**FIGURE 3. Expert and Crowd-sourced Estimates of Economic and Social Policy Positions**



# Crowd-sourced text analysis (Benoit et al, 2016 APSR)

**FIGURE 5. Standard Errors of Manifesto-level Policy Estimates as a Function of the Number of Workers, for the Oversampled 1987 and 1997 Manifestos**




*Note:* Each point is the bootstrapped standard deviation of the mean of means aggregate manifesto scores, computed from sentence-level random n subsamples from the codes.

# Evaluating the quality of a labeled set

Any labeled set should be tested and reported for its inter-rater reliability, also sometimes called inter-coder reliability, at three different standards:

| Type | Test Design | Causes of Disagreements | Strength |
|---|---|---|---|
| **Stability** | test-retest | intraobserver inconsistencies | weakest |
| **Reproducibility** | test-test | intraobserver inconsistencies + interobserver disagreements | medium |
| **Accuracy** | test-standard | intraobserver inconsistencies + interobserver disagreements + deviations from a standard | strongest |

# Measures of agreement

- Percent agreement Very simple:

  (number of agreeing ratings) / (total ratings) * 100%
- Correlation
  - (usually) Pearson's $r$, aka product-moment correlation
  - Formula: $r_{AB} = \frac{1}{n-1} \sum_{i=1}^{n} \left( \frac{A_i - \bar{A}}{s_A} \right) \left( \frac{B_i - \bar{B}}{s_B} \right)$
  - May also be ordinal, such as Spearman's rho or Kendall's tau-b
  - Range is [0,1]
- Agreement measures
  - Take into account not only observed agreement, but also *agreement that would have occured by chance*
  - Cohen's $\kappa$ is most common
  - Krippendorf's $\alpha$ is a generalization of Cohen's $\kappa$
  - Both range from [0,1]

# Reliability data matrixes

Example here used binary data (from Krippendorff)

| **Article:** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Coder A** | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Coder B** | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 |

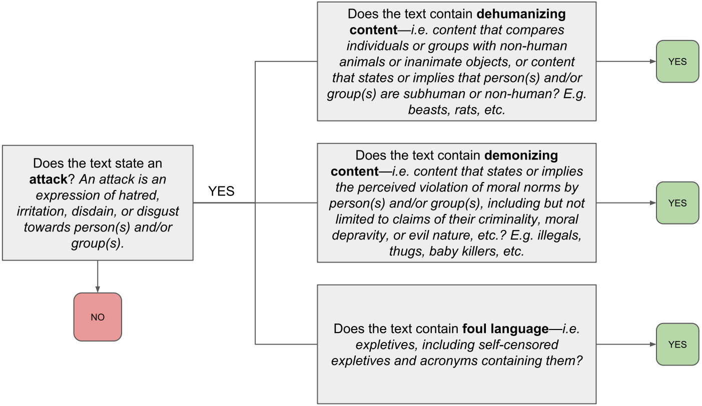
- A and B agree on 60% of the articles: 60% agreement
- Correlation is (approximately) 0.10
- Observed *dis*agreement: 4
- Expected *dis*agreement (by chance): 4.4211
- Krippendorff's $\alpha = 1 - \frac{D_o}{D_e} = 1 - \frac{4}{4.4211} = 0.095$
- Cohen's $\kappa$ (nearly) identical

given coder A labeled 2 and coder b 4, in random we expect that 4.4211 they will disagree with each other

# Example: Identifying Hate Speech

*NOTE: The content of an attack doesn't have to be objectively true or false for it to be an attack.*

## ATTACK



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# Basic principles of supervised learning

- Generalization: A classifier or a regression algorithm learns to correctly predict output from given inputs not only in previously seen samples but also in previously unseen samples
- Overfitting: A classifier or a regression algorithm learns to correctly predict output from given inputs in previously seen samples but fails to do so in previously unseen samples. This causes poor prediction/generalization.
- Goal is to maximize the frontier of precise identification of true condition with accurate recall

# Performance metrics

- Accuracy: How correctly is the classifier's identifications?
  - % of documents that are correctly predicted.
- Precision: Does the classifier identify *only* my content?
  - % of documents that are predicted positive that are indeed positive.
- Recall: Does the classifier identify *all* my content?
  - % of positive documents that are predicted positive.

# Performance metrics: confusion matrix

| | | True condition | |
|---|---|---|---|
| | | Positive | Negative |
| **Prediction** | Positive | True Positive | False Positive (Type I error) |
| | Negative | False Negative (Type II error) | True Negative |

- Accuracy: $\frac{\text{Correctly classified}}{\text{Total number of cases}} = \frac{\text{true positives} + \text{true negatives}}{\text{Total number of cases}}$
- Precision: $\frac{\text{true positives}}{\text{true positives} + \text{false positives}}$
- Recall: $\frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$
- $F1 \text{ score} = 2\,\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$
  (the harmonic mean of precision and recall)

how well does it balance precision and recall
specifically helpful when data is imbalanced

# Example: measuring performance

Assume:

- We have a corpus where 80 documents are really positive (as opposed to negative, as in sentiment)
- Our method declares that 60 are positive
- Of the 60 declared positive, 45 are actually positive

Solution:

$$\text{Precision} = (45/(45+15)) = 45/60 = 0.75$$
$$\text{Recall} = (45/(45+35)) = 45/80 = 0.56$$

F1 score = 2*(precision*recall)/(precision+recall) = 2*0.42/1.31 = 0.64

# Accuracy?

| | | True condition | | |
|---|---|---|---|---|
| | | Positive | Negative | |
| Prediction | Positive | 45 | | 60 |
| | Negative | | | |
| | | 80 | | |

# add in the cells we can compute

| | | True condition | | |
|---|---|---|---|---|
| | | Positive | Negative | |
| **Prediction** | Positive | 45 | *15* | 60 |
| | Negative | *35* | | |
| | | 80 | | |

# but need True Negatives and $N$ to compute accuracy

| | | **True condition** | | |
|---|---|---|---|---|
| | | Positive | Negative | |
| **Prediction** | Positive | 45 | *15* | 60 |
| | Negative | *35* | **???** | |
| | | 80 | | |

# assume 10 True Negatives:

| | | **True condition** | | |
|---|---|---|---|---|
| | | Positive | Negative | |
| **Prediction** | Positive | 45 | *15* | 60 |
| | Negative | *35* | ***10*** | ***45*** |
| | | 80 | ***25*** | ***105*** |

$$\text{Accuracy} = (45 + 10)/105 = 0.52$$

$$\text{F1} = 2 * (0.75 * 0.56)/(0.75 + 0.56) = 0.64$$

# now assume 100 True Negatives:

| | | True condition | | |
|---|---|---|---|---|
| | | Positive | Negative | |
| Prediction | Positive | 45 | *15* | 60 |
| | Negative | *35* | ***100*** | ***135*** |
| | | 80 | ***115*** | ***195*** |

$$\text{Accuracy} = (45 + 100)/195 \qquad = 0.74$$

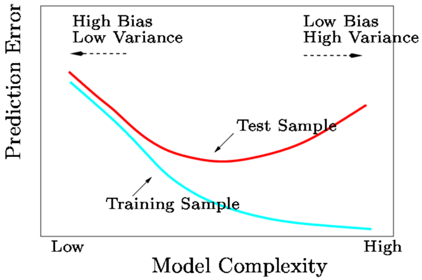
$$\text{F1} = 2 * (0.75 * 0.56)/(0.75 + 0.56) \qquad = 0.64$$

# Measuring performance

- Precision and recall can be reported separately for each category
- Precision and recall (or F1) should be reported alongside accuracy. Why?
- There is generally a trade-off between precision and recall. Why?

# Measuring performance

- Classifier is trained to maximize in-sample performance
- But generally we want to apply method to new data
- Danger: overfitting



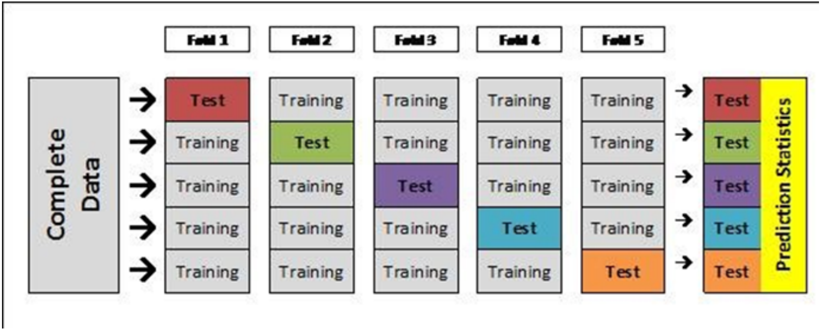

- Model is too complex, describes noise rather than signal (Bias-Variance trade-off)
- Focus on features that perform well in labeled data but may not generalize (e.g. "inflation" in 1980s)
- In-sample performance better than out-of-sample performance

- Solutions?
  - Randomly split dataset into training and test set
  - Cross-validation

# Cross-validation

Intuition:

- Create K training and test sets (“folds”) within training set.
- For each k in K, run classifier and estimate performance in test set within fold.
- Choose best classifier based on cross-validated performance



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# Multinomial Bayes model of Class given a Word

Consider $J$ word types distributed across $N$ documents, each assigned one of $K$ classes.

*At the word level*, Bayes Theorem tells us that:

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j)}$$

For two classes, this can be expressed as

$$= \frac{P(w_j|c_k)P(c_k)}{P(w_j|c_k)P(c_k) + P(w_j|c_{\neg k})P(c_{\neg k})} \tag{1}$$

# Multinomial Bayes model of Class given a Word

## Class-conditional word likelihoods

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j|c_k)P(c_k) + P(w_j|c_{\neg k})P(c_{\neg k})}$$

- The word likelihood within class
- The maximum likelihood estimate is simply the proportion of times that word $j$ occurs in class $k$, but it is more common to use Laplace smoothing by adding 1 to each observed count within class

# Multinomial Bayes model of Class given a Word

## Word probabilities

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j)}$$

- This represents the word probability from the training corpus
- Usually uninteresting, since it is constant for the training data; is independent of the class $k$.
- This is called a scaling factor and is only needed to compute posteriors on a probability scale.

# Multinomial Bayes model of Class given a Word
## Class prior probabilities

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j|c_k)P(c_k) + P(w_j|c_{\neg k})P(c_{\neg k})}$$

- This represents the class prior probability
- Machine learning typically takes this as the document frequency in the training set

# Multinomial Bayes model of Class given a Word

## Class posterior probabilities

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j|c_k)P(c_k) + P(w_j|c_{\neg k})P(c_{\neg k})}$$

- This represents the posterior probability of membership in class $k$ for word $j$
- Key for the classifier: in new documents, we only observe word distributions and want to predict class

# Moving to the document level

- The "Naive" Bayes model of a joint document-level class posterior assumes conditional independence, to multiply the word likelihoods from a "test" document, to produce:

$$P(c_k|d) = P(c_k) \prod_{j}^{J} \frac{P(w_j|c_k)}{P(w_j)}$$

$$P(c_k|d) \propto P(c_k) \prod_{j}^{J} P(w_j|c_k)$$

- This is why we call it "naive": because it (wrongly) assumes:
  - conditional independence of word counts given the class.
    - If the word "weather" appears in a document, it is more likely that we will see words like "forecast" and "report"
  - positional independence of word counts (bag of words assumption)
    - It is meaningful for words like "not" and "good" to be close together.
    - "Peace, no more war", "War, no more peace" (Source: Arthur Spirling)

# Naive Bayes Classification Example

(From Manning, Raghavan and Schütze, *Introduction to Information Retrieval*)

► **Table 13.1** Data for parameter estimation examples.

| | docID | words in document | in $c = China$? |
|---|---|---|---|
| training set | 1 | Chinese Beijing Chinese | yes |
| | 2 | Chinese Chinese Shanghai | yes |
| | 3 | Chinese Macao | yes |
| | 4 | Tokyo Japan Chinese | no |
| test set | 5 | Chinese Chinese Chinese Tokyo Japan | ? |

# Naive Bayes Classification Example

**Example 13.1:** For the example in Table 13.1, the multinomial parameters we need to classify the test document are the priors $\hat{P}(c) = 3/4$ and $\hat{P}(\overline{c}) = 1/4$ and the following conditional probabilities:

six unique words in our training data

$$
\begin{aligned}
\hat{P}(\text{Chinese}|c) &= (5+1)/(8+6) = 6/14 = 3/7 \\
\hat{P}(\text{Tokyo}|c) = \hat{P}(\text{Japan}|c) &= (0+1)/(8+6) = 1/14 \\
\hat{P}(\text{Chinese}|\overline{c}) &= (1+1)/(3+6) = 2/9 \\
\hat{P}(\text{Tokyo}|\overline{c}) = \hat{P}(\text{Japan}|\overline{c}) &= (1+1)/(3+6) = 2/9
\end{aligned}
$$

The denominators are $(8+6)$ and $(3+6)$ because the lengths of $text_c$ and $text_{\overline{c}}$ are 8 and 3, respectively, and because the constant $B$ in Equation (13.7) is 6 as the vocabulary consists of six terms.

We then get:

$$
\begin{aligned}
\hat{P}(c|d_5) &\propto 3/4 \cdot (3/7)^3 \cdot 1/14 \cdot 1/14 \approx 0.0003. \\
\hat{P}(\overline{c}|d_5) &\propto 1/4 \cdot (2/9)^3 \cdot 2/9 \cdot 2/9 \approx 0.0001.
\end{aligned}
$$

Thus, the classifier assigns the test document to $c$ = *China*. The reason for this classification decision is that the three occurrences of the positive indicator Chinese in $d_5$ outweigh the occurrences of the two negative indicators Japan and Tokyo.

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# Regularized regression

Assume we have:

- $i = 1, 2, \ldots, N$ documents
- Each document $i$ is in class $y_i = 0$ or $y_i = 1$
- $j = 1, 2, \ldots, J$ unique features
- And $x_{ij}$ as the count of feature $j$ in document $i$

We could build a linear regression model as a classifier, using the values of $\beta_0$, $\beta_1$, ..., $\beta_J$ that minimize:

$$RSS = \sum_{i=1}^{N} \left( y_i - \beta_0 - \sum_{j=1}^{J} \beta_j x_{ij} \right)^2$$

But can we?

- If $J > N$, OLS does not have a unique solution
- Even with $N > J$, OLS has low bias/high variance (overfitting)

# Regularized regression

What can we do? Add a penalty for model complexity, such that we now minimize:

to handle overfitting

$$\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{J}\beta_j x_{ij}\right)^2 + \lambda \sum_{j=1}^{J}\beta_j^2 \rightarrow \text{ridge regression}$$

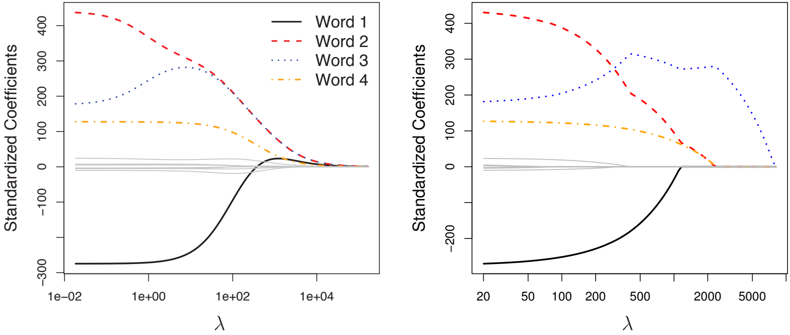
what you need to tune through cross validation

or

$$\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{J}\beta_j x_{ij}\right)^2 + \lambda \sum_{j=1}^{J}|\beta_j| \rightarrow \text{lasso regression}$$

where $\lambda$ is the **penalty parameter** (to be estimated)

# Visualizing Lasso vs. Ridge Regression




- We penalize large coefficients more as the size of $\lambda$ increases
- Ridge regression shrinks some parameters close to zero but never quite gets there.
- Lasso shrinks some parameters to exactly zero.
  it is actually performing feature seleciton

# Regularized regression

Why the penalty (shrinkage)?

- Reduces the variance better applying to out of sample data
- Identifies the model if J $>$ N
- Some coefficients become zero (feature selection)

The penalty can take different forms:

- Ridge regression: $\lambda \sum_{j=1}^{J} \beta_j^2$ with $\lambda > 0$; and when $\lambda = 0$ becomes OLS
- Lasso $\lambda \sum_{j=1}^{J} |\beta_j|$ where some coefficients become zero.
- Elastic Net: $\lambda_1 \sum_{j=1}^{J} \beta_j^2 + \lambda_2 \sum_{j=1}^{J} |\beta_j|$ (best of both worlds?)

How to find best value of $\lambda$? Cross-validation.
Evaluation: regularized regression is easy to interpret, but often outperformed by more complex methods.

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# Motivating Example: Government Astroturfer Detection

## The Fifty Cent Party


"Netizens first coined the term 'Fifty Cent Party' to refer to undercover Internet commentators paid by the government to sway public opinion ('fifty cents' is a reference to the alleged pay received per post)."

—China Digital Times

# Motivating Example: Government Astroturfer Detection

Amazon review astroturfing exhibit from the Amazon v. Gentile lawsuit in Washington Superior Court.

**Cool charger**
By Tiffany on March 30, 2015
Verified Purchase
Bought this for my Galaxy phone and I have to say, this is a pretty cool USB cord! :) I like the lights in the cord as it puts off a cool glowing effect in my room at night and it makes it much easier to see, thanks for the great product!

**Definitely buying more.**
By Krystal Willingham on March 28, 2015
Verified Purchase
I was impressed with how bright the lights on the cable are. It works amazing and as described. i received earlier than expected so that made me very happy. So far is working like a charm and I can't wait to buy a few more.

- *Research Challenge:* Need to disambiguate government astroturfers and non-government astroturfers
- *Potential Solution:* Use information from the social network of users. Do they follow government accounts?

# Motivating Example: Government Astroturfer Detection

Local government leaders are evaluated for promotion based on their online influence.

| Rank | Weibo Name | Weibo Description/Affiliation | Message Reach | Public Service | Inter-activity | Public Acceptance | Overall Score |
|---|---|---|---|---|---|---|---|
| 1 | Xinjiang Earthquake Administration | Official Weibo Account of the Xinjiang Earthquake Administration | 74.11 | 74.78 | 74.02 | 78.99 | 74.84 |
| 2 | Rapid Road Traffic Police | Official Weibo Account of the Urumqi City Rapid Road Traffic Police | 72.75 | 81.73 | 58.03 | 59.14 | 70.56 |
| 3 | Peaceful Shihezi | Official Weibo Account of the Shihezi City Public Security Bureau | 58.97 | 86.68 | 53.83 | 54.19 | 68.04 |
| 4 | Xinjiang Railways | Official Weibo Account of the Urumqi Railway Administration | 63.94 | 81.00 | 47.14 | 51.89 | 64.52 |
| 5 | Altay Online Public Security | Official Weibo Account of the Xinjiang Uighur Autonomous Region Altay Public Security Bureau | 65.44 | 57.62 | 69.06 | 70.90 | 63.95 |
| 6 | Xinjiang Anti-Cult | Official Weibo of the Office of the Leading Group for the Prevention and Treatment of Cults in Xinjiang Uygur Autonomous Region | 62.44 | 51.90 | 64.17 | 60.95 | 60.70 |
| 7 | Peaceful Xinjiang Online | Official Weibo Account of the Xinjiang Provincial Public Security Bureau | 48.29 | 66.99 | 57.78 | 52.21 | 55.27 |
| 8 | Xinjiang Fire Corps | Official Weibo Account of the Xinjiang Fire Corps | 55.98 | 60.89 | 49.51 | 39.97 | 54.40 |
| 9 | Hetian Internet Police Inspection and Law Enforcement | Official Weibo Account of the Xinjiang Hetian District Public Security Bureau Network Security Detachment | 56.68 | 61.78 | 48.83 | 27.95 | 53.49 |
| 10 | Changji Fire Brigade | Official Weibo Account of the Xinjiang Changji Prefecture Public Security Fire Brigade | 55.71 | 60.03 | 45.57 | 43.96 | 53.22 |

Central government rankings of Weibo accounts in Xinjiang Province

# Motivating Example: Government Astroturfer Detection

Bureaucrats are often required to follow the account of the Document from a local propaganda department email leak.

| Zhanggong District Dept. of Education<br>Followers of Zhanggong Propaganda Department Weibo Account | | | | |
|---|---|---|---|---|
| Index | School (Work Unit) | Name | Weibo Username | Have they followed? |
| 1 | Ganzhou No.7 Middle School | [illegible] | [illegible] | Yes |
| 2 | Ganzhou No.7 Middle School | [illegible] | [illegible] | Yes |
| 3 | Ganzhou No.7 Middle School | [illegible] | [illegible] | Yes |
| 4 | Ganzhou No.7 Middle School | [illegible] | [illegible] | Yes |
| 5 | Ganzhou No.7 Middle School | [illegible] | [illegible] | Yes |
| 6 | Ganzhou Cuo'e Temple Elementary School | [illegible] | [illegible] | Yes |

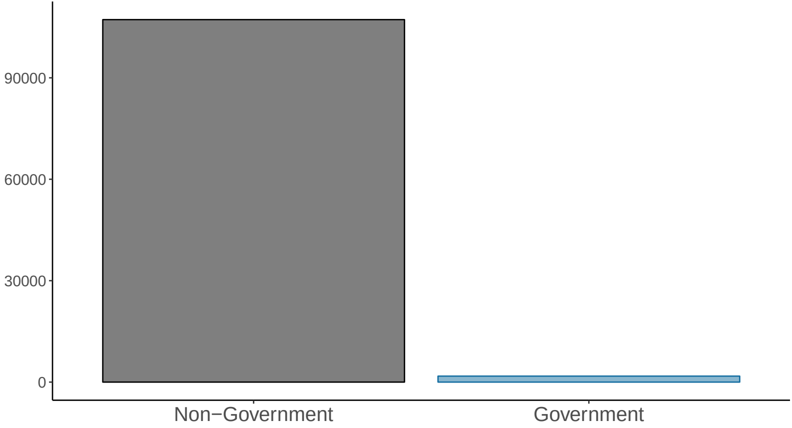
Document from a local propaganda department email leak.

# Motivating Example: Classifying Government Accounts

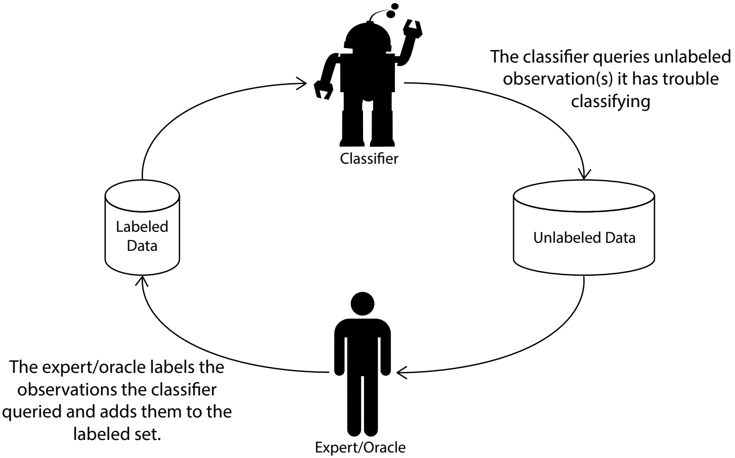
- Need to automatically classify Weibo accounts as government and non-government.
- Build a training set of Weibo accounts using active learning.
- Use this training sample to classify all followed accounts in a corpus of  80 million news comments.

# Motivating Example: Classifying Government Accounts

One major concern: the two classes for this problem are highly imbalanced.



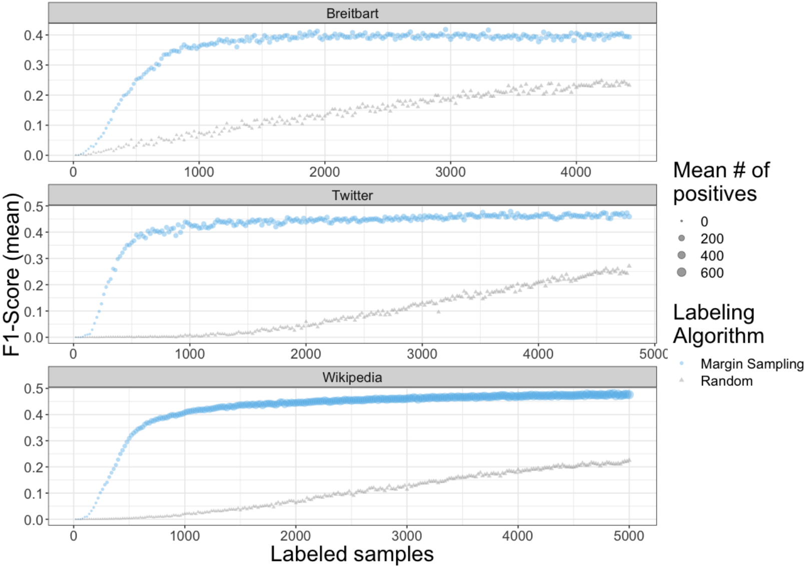
# A Potential Solution: Active Learning



# Active Learning (details)

- For supervised learning, we need human labels for a subset of documents.
  - This can be expensive and time consuming, especially when classes are imbalanced (e.g. government vs. non-government social media accounts)
- Active learning instead samples observation based on an uncertainty measure derived from one or more classifiers.
  - Logic: Rather than wasting effort on easily classifiable observations, focus on the hard cases.
  - Many potential uncertainty measures (e.g. observations with $p \approx .5$ for a logit model)
- Active learning can dramatically decrease the number of observations we must label for supervised learning (Miller et. al., 2020)
- Caveat: Error measures will be biased; should use randomly sampled test set to compute error.

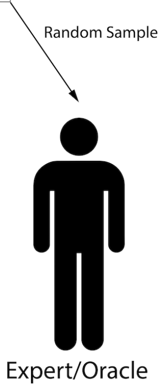
# Comparing Active and Passive Learning




Source: Miller et. al. (2020)

# Passive Learning

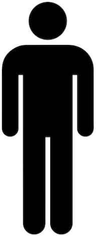
| | Party | government | good | football | China | ... |
|---|---|---|---|---|---|---|
| $X_1$ | 8 | 9 | 5 | 0 | 12 | ... |
| $X_2$ | 0 | 0 | 8 | 4 | 0 | ... |
| $X_3$ | 0 | 0 | 7 | 4 | 2 | ... |
| $X_4$ | 9 | 8 | 6 | 0 | 8 | ... |
| ... | ... | ... | ... | ... | ... | ... |



# Passive Learning

| | Party | government | good | football | China | ... |
|---|---|---|---|---|---|---|
| $X_1$ | 8 | 9 | 5 | 0 | 12 | ... |
| $X_2$ | 0 | 0 | 8 | 4 | 0 | ... |
| $X_3$ | 0 | 0 | 7 | 4 | 2 | ... |
| $X_4$ | 9 | 8 | 6 | 0 | 8 | ... |
| ... | ... | ... | ... | ... | ... | ... |

Random Sample



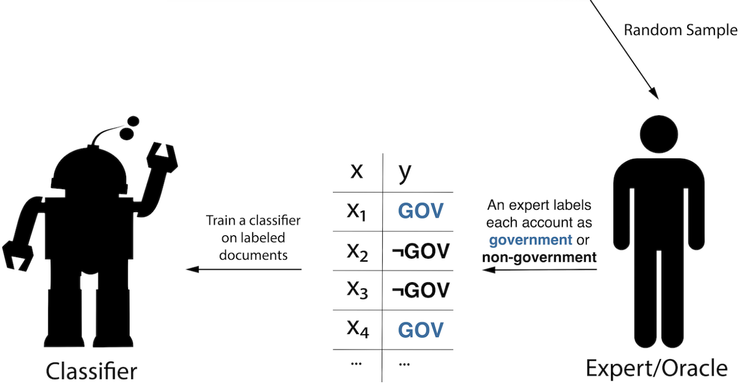
Expert/Oracle

An expert labels each account as **government** or **non-government**

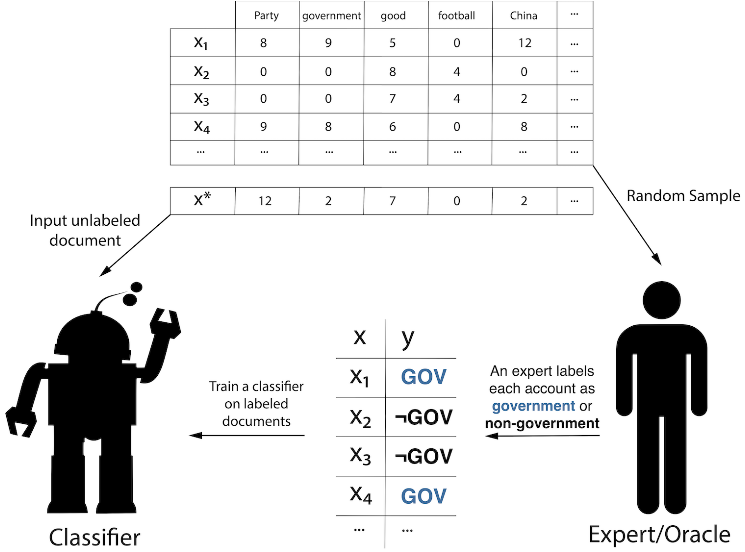
| x | y |
|---|---|
| $X_1$ | **GOV** |
| $X_2$ | **¬GOV** |
| $X_3$ | **¬GOV** |
| $X_4$ | **GOV** |
| ... | ... |

# Passive Learning

| | Party | government | good | football | China | ... |
|---|---|---|---|---|---|---|
| $x_1$ | 8 | 9 | 5 | 0 | 12 | ... |
| $x_2$ | 0 | 0 | 8 | 4 | 0 | ... |
| $x_3$ | 0 | 0 | 7 | 4 | 2 | ... |
| $x_4$ | 9 | 8 | 6 | 0 | 8 | ... |
| ... | ... | ... | ... | ... | ... | ... |



# Passive Learning

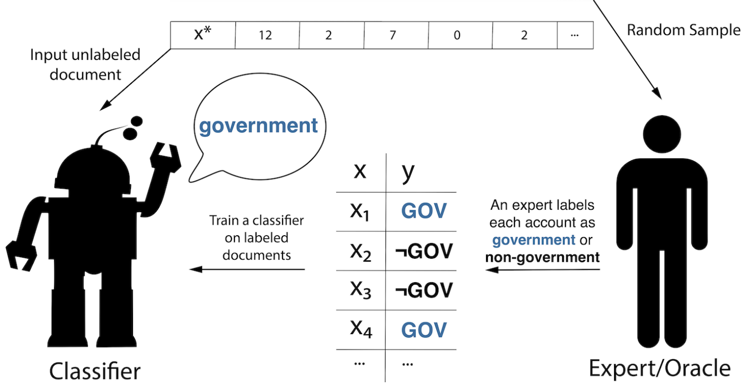



| | Party | government | good | football | China | ... |
|---|---|---|---|---|---|---|
| $x_1$ | 8 | 9 | 5 | 0 | 12 | ... |
| $x_2$ | 0 | 0 | 8 | 4 | 0 | ... |
| $x_3$ | 0 | 0 | 7 | 4 | 2 | ... |
| $x_4$ | 9 | 8 | 6 | 0 | 8 | ... |
| ... | ... | ... | ... | ... | ... | ... |
| $x^*$ | 12 | 2 | 7 | 0 | 2 | ... |

| x | y |
|---|---|
| $x_1$ | GOV |
| $x_2$ | ¬GOV |
| $x_3$ | ¬GOV |
| $x_4$ | GOV |
| ... | ... |

# Passive Learning

| | Party | government | good | football | China | ... |
|---|---|---|---|---|---|---|
| $x_1$ | 8 | 9 | 5 | 0 | 12 | ... |
| $x_2$ | 0 | 0 | 8 | 4 | 0 | ... |
| $x_3$ | 0 | 0 | 7 | 4 | 2 | ... |
| $x_4$ | 9 | 8 | 6 | 0 | 8 | ... |
| ... | ... | ... | ... | ... | ... | ... |
| $x^*$ | 12 | 2 | 7 | 0 | 2 | ... |

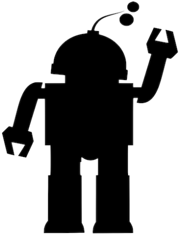



| x | y |
|---|---|
| $x_1$ | GOV |
| $x_2$ | ¬GOV |
| $x_3$ | ¬GOV |
| $x_4$ | GOV |
| ... | ... |

# Active Learning

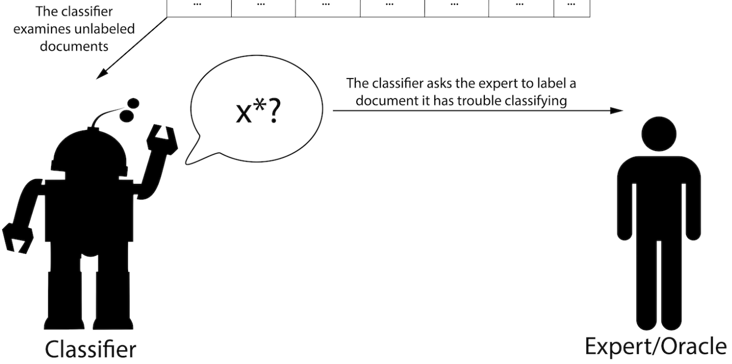
| | Party | government | good | football | China | ... |
|---|---|---|---|---|---|---|
| $X_1$ | 8 | 9 | 5 | 0 | 12 | ... |
| $X_2$ | 0 | 0 | 8 | 4 | 0 | ... |
| $X_3$ | 0 | 0 | 7 | 4 | 2 | ... |
| $X_4$ | 9 | 8 | 6 | 0 | 8 | ... |
| ... | ... | ... | ... | ... | ... | ... |

The classifier examines unlabeled documents



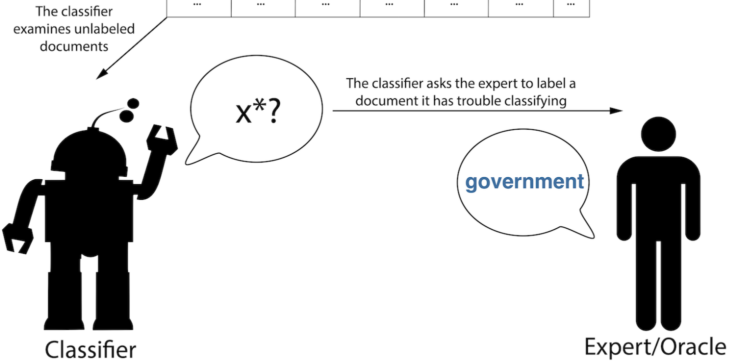
# Active Learning

| | Party | government | good | football | China | ... |
|---|---|---|---|---|---|---|
| $x_1$ | 8 | 9 | 5 | 0 | 12 | ... |
| $x_2$ | 0 | 0 | 8 | 4 | 0 | ... |
| $x_3$ | 0 | 0 | 7 | 4 | 2 | ... |
| $x_4$ | 9 | 8 | 6 | 0 | 8 | ... |
| ... | ... | ... | ... | ... | ... | ... |



# Active Learning

| | Party | government | good | football | China | ... |
|---|---|---|---|---|---|---|
| $x_1$ | 8 | 9 | 5 | 0 | 12 | ... |
| $x_2$ | 0 | 0 | 8 | 4 | 0 | ... |
| $x_3$ | 0 | 0 | 7 | 4 | 2 | ... |
| $x_4$ | 9 | 8 | 6 | 0 | 8 | ... |
| ... | ... | ... | ... | ... | ... | ... |



# Example: Classifying Government Accounts

Model performance (F1): 0.93

Avatars of predicted government accounts.

# Outline

- Supervised learning overview
- Creating a labeled set and evaluating its reliability
- Classifier performance metrics
- Examples of classifiers
  - Naive Bayes
  - Regularized regression
- Active learning for labeling texts
- Applications of classifiers in social science research

# Example: Theocharis et al (2016 JOC)

Why do politicians not take full advantage of interactive affordances of social media?

A politician's incentive structure

Democracy $\rightarrow$ Dialogue $>$ Mobilisation $>$ Marketing

Politician $\rightarrow$ Marketing $>$ Mobilisation $>$ Dialogue*

H1: Politicians make broadcasting rather than engaging use of Twitter

H2: Engaging style of tweeting is positively related to impolite or uncivil responses

# Data collection and case selection

Data: European Election Study 2014, Social Media Study

- List of all candidates with Twitter accounts in 28 EU countries
  - 2,482 out of 15,527 identified MEP candidates (16%)
- Collaboration with TNS Opinion to collect all tweets by candidates *and* tweets mentioning candidates (tweets, retweets, @-replies), May 5th to June 1st 2014.

Case selection: expected variation in politeness/civility

| | Received bailout | Did not receive bailout |
|---|---|---|
| High support for EU | Spain (55.4%) | Germany (68.5%) |
| Low support for EU | Greece (43.8%) | UK (41.4%) |

(% indicate proportion of country that considers the EU to be “a good thing”)

# Data collection and case selection

### Data coverage by country

| Country | Lists | Candidates | on Twitter | Tweets |
|---|---|---|---|---|
| Germany | 9 | 501 | 123 (25%) | 86,777 |
| Greece | 9 | 359 | 99 (28%) | 18,709 |
| Spain | 11 | 648 | 221 (34%) | 463,937 |
| UK | 28 | 733 | 304 (41%) | 273,886 |

# Coding tweets

Coded data: random sample of ∼7,000 tweets from each country, labeled by undergraduate students:

1. **Politeness**
   - Polite: tweet adheres to politeness standards.
   - Impolite: ill-mannered, disrespectful, offensive language...
2. **Communication style**
   - Broadcasting: statement, expression of opinion
   - Engaging: directed to someone else/another user
3. **Political content: moral and democracy**
   - Tweets make reference to: freedom and human rights, traditional morality, law and order, social harmony, democracy...

**Incivility** = impoliteness + moral and democracy

# Coding tweets

Coding process: summary statistics

| | Germany | Greece | Spain | UK |
|---|---|---|---|---|
| Coded by 1/by 2 | 2947/2819 | 2787/2955 | 3490/1952 | 3189/3296 |
| Total coded | 5766 | 5742 | 5442 | 6485 |
| Impolite | 399 | 1050 | 121 | 328 |
| Polite | 5367 | 4692 | 5321 | 6157 |
| % Agreement | 92 | 80 | 93 | 95 |
| Krippendorf/Maxwell | 0.30/0.85 | 0.26/0.60 | 0.17/0.87 | 0.54/0.90 |
| Broadcasting | 2755 | 2883 | 1771 | 1557 |
| Engaging | 3011 | 2859 | 3671 | 4928 |
| % Agreement | 79 | 85 | 84 | 85 |
| Krippendorf/Maxwell | 0.58/0.59 | 0.70/0.70 | 0.66/0.69 | 0.62/0.70 |
| Moral/Dem. | 265 | 204 | 437 | 531 |
| Other | 5501 | 5538 | 5005 | 5954 |
| % Agreement | 95 | 97 | 96 | 90 |
| Krippendorf/Maxwell | 0.50/0.91 | 0.53/0.93 | 0.41/0.92 | 0.39/0.81 |

# Machine learning classification of tweets

Coded tweets as training dataset for a machine learning classifier:

1. Text preprocessing: lowercase, remove stopwords and punctuation (except # and @), transliterating to ASCII, stem, tokenize into unigrams and bigrams. Keep tokens in 2+ tweets but <90%.
2. Train classifier: logistic regression with L2 regularization (ridge regression), one per language and variable
3. Evaluate classifier: compute accuracy using 5-fold crossvalidation

# Machine learning classification of tweets

Classifier performance (5-fold cross-validation)

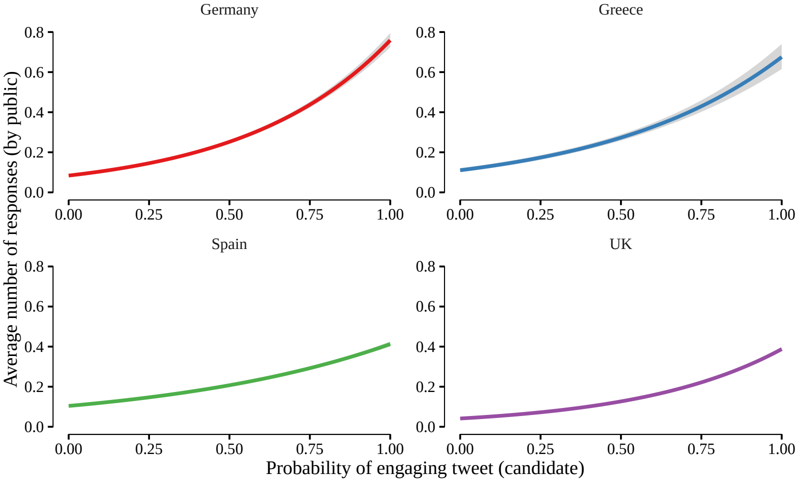
| | | UK | Spain | Greece | Germany |
|---|---|---|---|---|---|
| Communication Style | Accuracy | 0.821 | 0.775 | 0.863 | 0.806 |
| | Precision | 0.837 | 0.795 | 0.838 | 0.818 |
| | Recall | 0.946 | 0.890 | 0.894 | 0.832 |
| Polite vs. impolite | Accuracy | 0.954 | 0.976 | 0.821 | 0.935 |
| | Precision | 0.955 | 0.977 | 0.849 | 0.938 |
| | Recall | 0.998 | 1.000 | 0.953 | 0.997 |
| Morality and Democracy | Accuracy | 0.895 | 0.913 | 0.957 | 0.922 |
| | Precision | 0.734 | 0.665 | 0.851 | 0.770 |
| | Recall | 0.206 | 0.166 | 0.080 | 0.061 |

## Top predictive n-grams

| | |
|---|---|
| Broadcasting | just, hack, #votegreen2014, :, and, @ ', tonight, candid, up, tonbridg, vote @, im @, follow ukip, ukip @, #telleurop, angri, #ep2014, password, stori, #vote2014, team, #labourdoorstep, crimin, bbc news |
| Engaging | @ thank, @ ye, you'r, @ it', @ mani, @ pleas, u, @ hi, @ congratul, :), index, vote # skip, @ good, fear, cheer, haven't, lol, @ i'v, you'v, @ that', choice, @ wa, @ who, @ hope |
| Impolite | cunt, fuck, twat, stupid, shit, dick, tit, wanker, scumbag, moron, cock, foot, racist, fascist, sicken, fart, @ fuck, ars, suck, nigga, nigga ?, smug, idiot, @arsehol, arsehol |
| Polite | @ thank, eu, #ep2014, thank, know, candid, veri, politician, today, way, differ, europ, democraci, interview, time, tonight, @ think, news, european, sorri, congratul, good, :, democrat, seat |
| Moral/Dem. | democraci, polic, freedom, media, racist, gay, peac, fraud, discrimin, homosexu, muslim, equal, right, crime, law, violenc, constitut, faith, bbc, christian, marriag, god, cp, racism, sexist |
| Others | @ ha, 2, snp, nice, tell, eu, congratul, campaign, leav, alreadi, wonder, vote @, ;), hust, nh, brit, tori, deliv, bad, immigr, #ukip, live, count, got, roma |

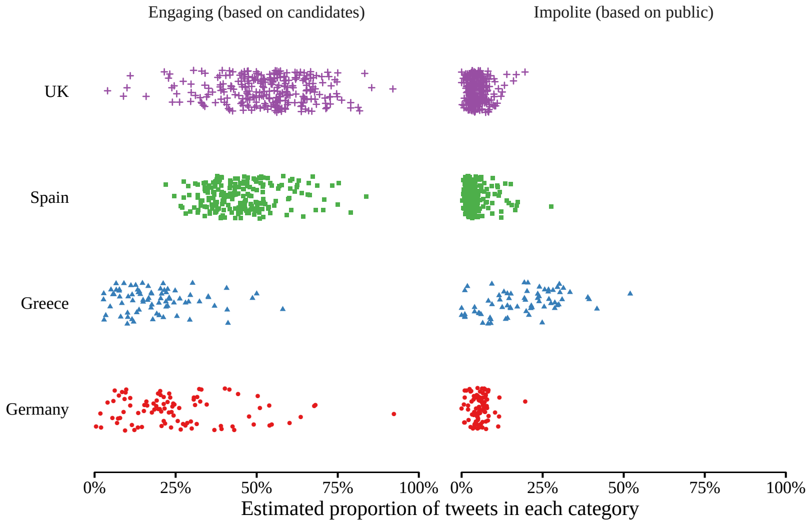
# Predictive validity

Citizens are more likely to respond to candidates when they adopt an engaging style



# Results: H1

## Proportion of engaging tweets sent and impolite tweets received, by candidate and country



# Results: H2

Is engaging style positively related to impolite responses?

Three levels of analysis:

1. **Across candidates**: candidates who send more engaging tweets receive more impolite responses.
2. **Within candidates, over time**: the number of impolite responses increases during the campaign for candidates who send more engaging tweets
3. **Across tweets**: tweets that are classified as engaging tend to receive more impolite responses