Quantitative text analysis: Machine Learning for Text

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MY 459: Quantitative Text Analysis

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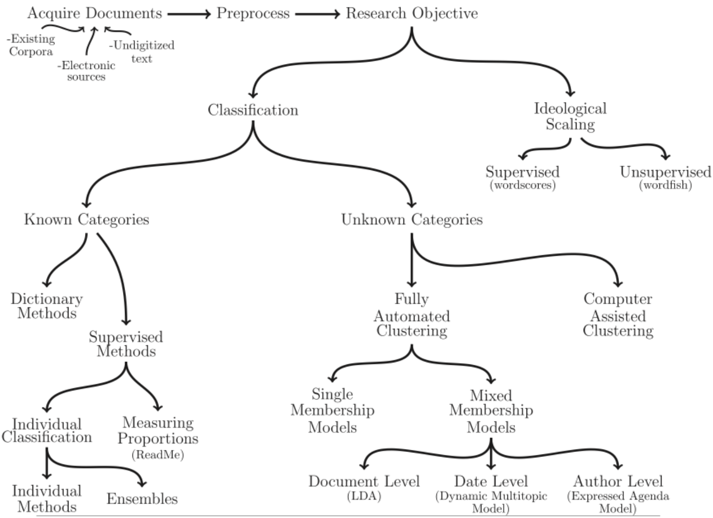
Course website: lse-my459.github.io

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
- Applications of classifiers in social science research
- Examples of classifiers (next week)

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...

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

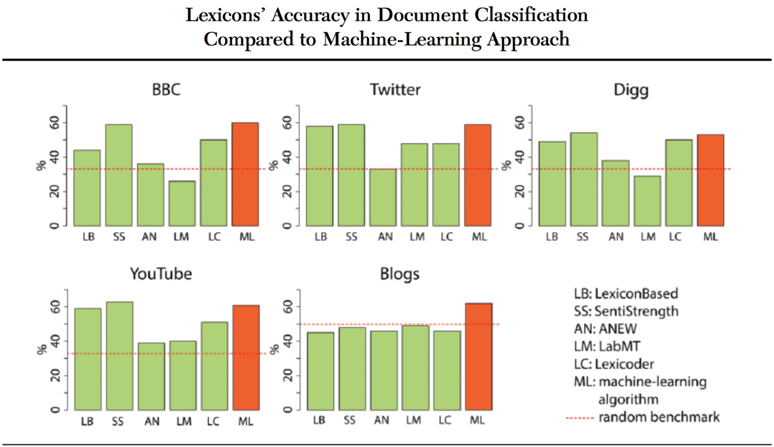
Supervised v. unsupervised methods: Examples

- 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

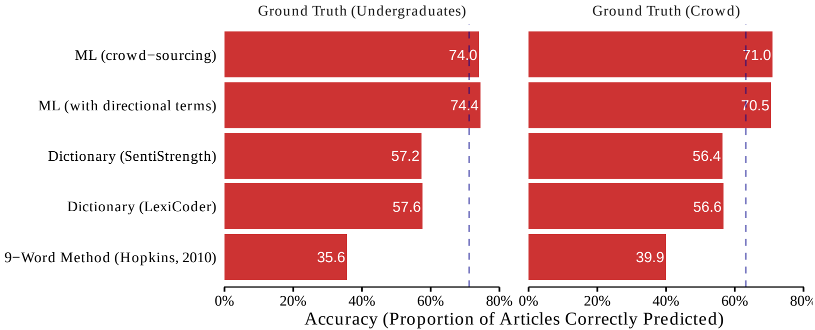
Dictionaries vs supervised learning



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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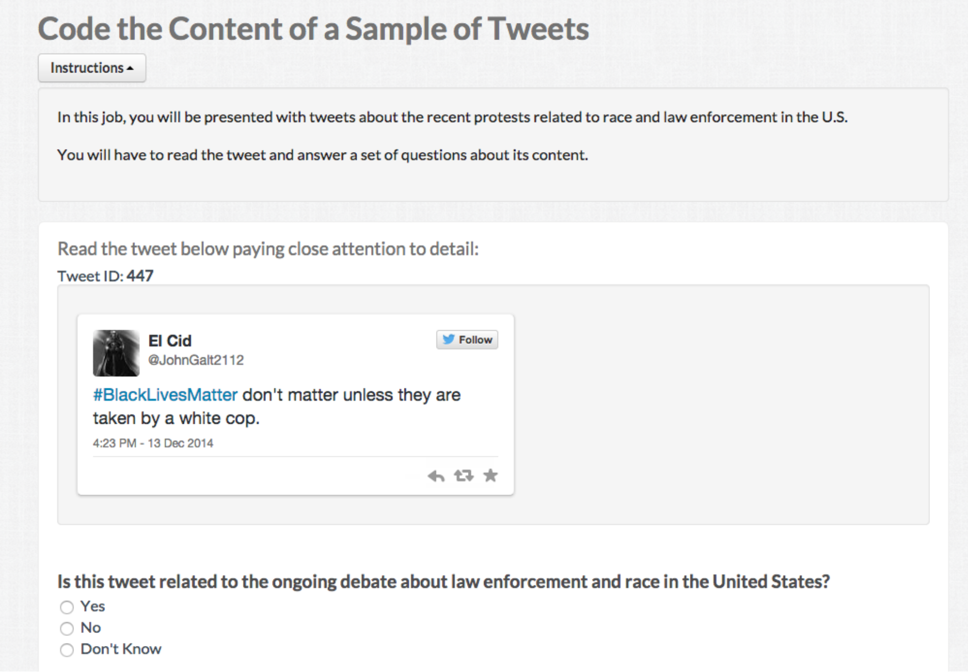
Creating a labeled set

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.

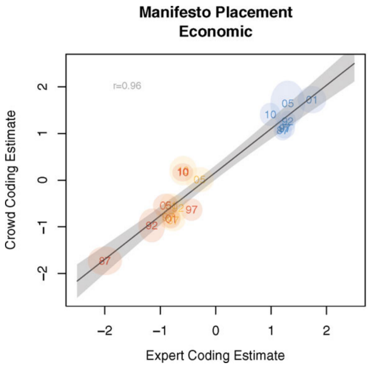
4:23 PM - 13 Dec 2014

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

- ◯ Yes
- ◯ No
- ◯ Don't Know

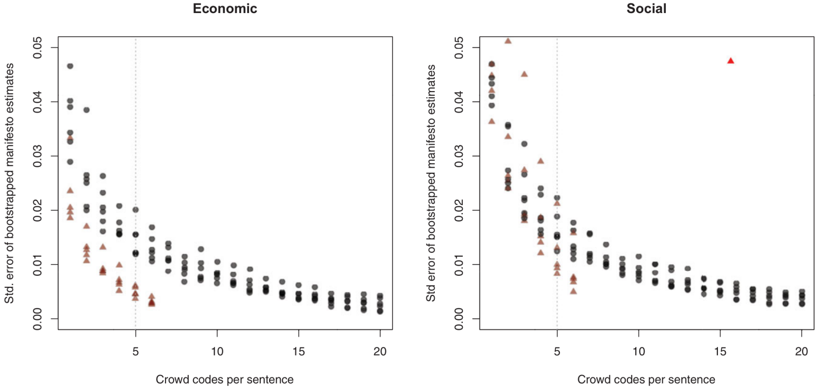
Crowd-sourced text analysis (Benoit et al, 2016 APSR)

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 κ is most common
  - Krippendorf's α is a generalization of Cohen's κ
  - Both range from [0,1]

Reliability data matrixes

Example here used binary data (from Krippendorff)

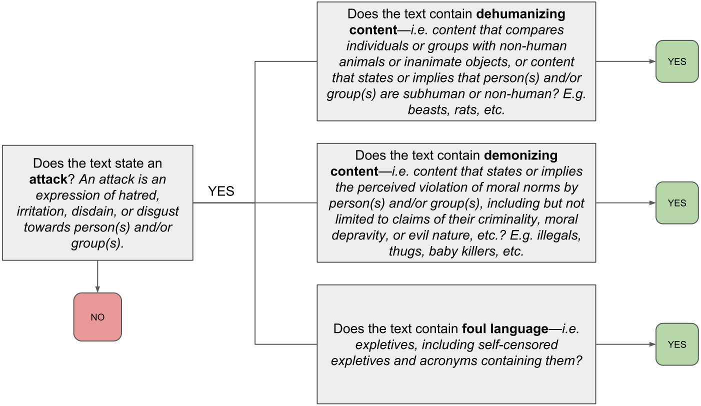
Article:	1	2	3	4	5	6	7	8	9	10
Coder A	1	1	0	0	0	0	0	0	0	0
Coder B	0	1	1	0	0	1	0	1	0	0

- 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 κ (nearly) identical

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

		True condition	
		Positive	Negative
Prediction	Positive	True Positive	False Positive (Type I error)

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:

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

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***

$$\text{Accuracy} = (45 + 10)/105 \qquad = 0.52$$
$$\text{F1} = 2 * (0.75 * 0.56)/(0.75 + 0.56) \qquad = 0.64$$

now assume 100 True Negatives:

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

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

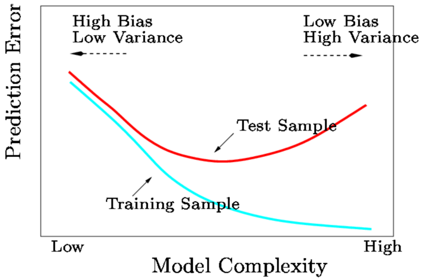
$$\text{F1} = 2 * (0.75 * 0.56)/(0.75 + 0.56) \qquad = 0.64$$

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



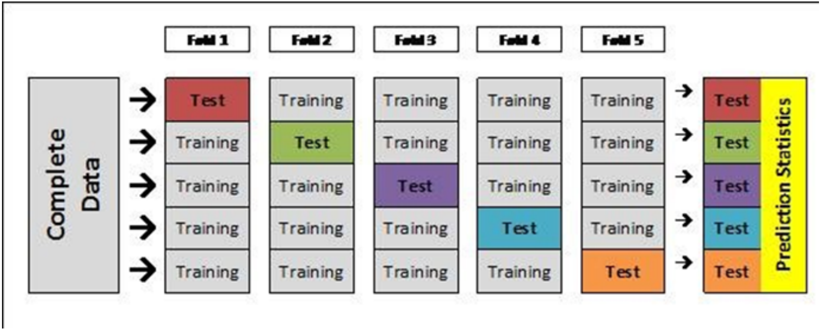
- Model is too complex, describes noise rather than signal (Bias-Variance trade-off)
- Focus on features that perform well in labeled data but may not generalize (e.g. "inflation" in 1980s)
- In-sample performance better than out-of-sample performance

- 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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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)

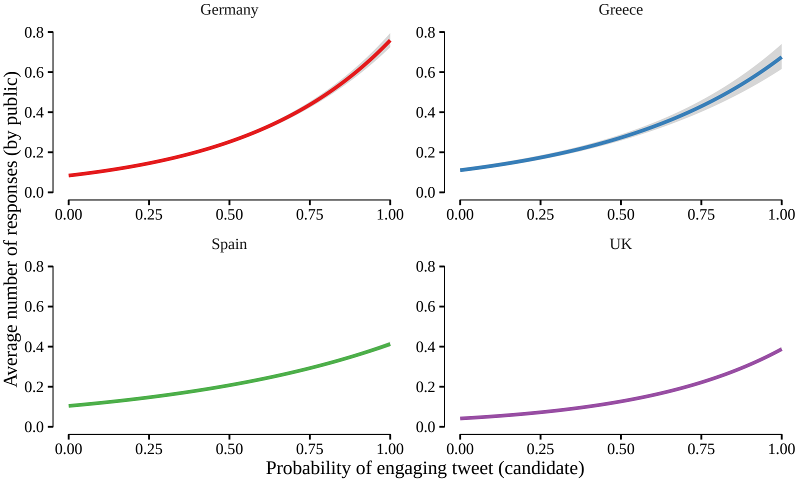
		UK	Spain	Greece	Germany
Communication Style	Accuracy	0.821	0.775	0.863	0.806
	Precision	0.837	0.795	0.838	0.818
	Recall	0.946	0.890	0.894	0.832
Polite vs. impolite	Accuracy	0.954	0.976	0.821	0.935
	Precision	0.955	0.977	0.849	0.938
	Recall	0.998	1.000	0.953	0.997
Morality and Democracy	Accuracy	0.895	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

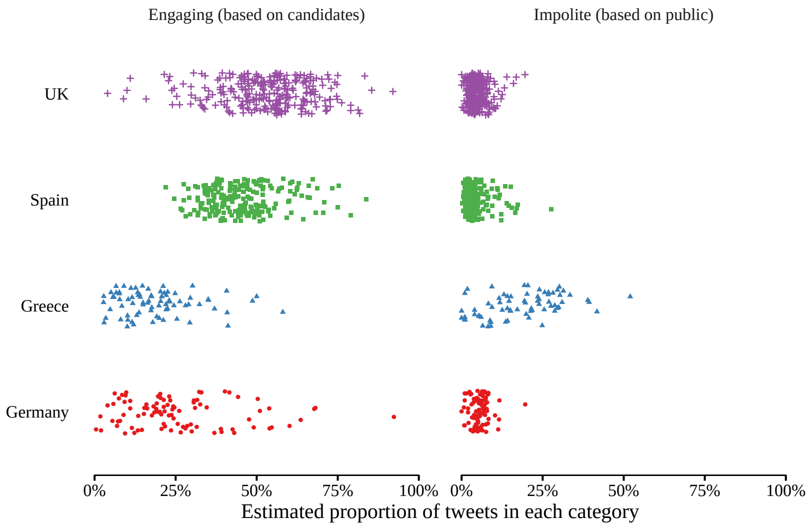
Predictive validity

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

Example: Astroturfer Detection

Astroturfing refers to any fake or staged "grassroots" activity.

Example: 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

Example: Astroturfer Detection

Astroturfing refers to any fake or staged "grassroots" activity.

- Research Questions:
  - What are Chinese government astroturfers saying?
  - What are the logics of government astroturfing campaigns?
- Method:
  - Use metadata rather than the comment text to match expected behavioral patterns of astroturfers.

Example: 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?

Example: Astroturfer Detection

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

排名	微博	认证信息	传播力	服务力	互动力	认同度	总分
1	新疆地震局	新疆地震局官方微博	74.11	74.78	74.02	78.99	74.84
2	快速路交警	乌鲁木齐市城市快速路交警大队官方微博	72.75	81.73	58.03	59.14	70.56
3	平安石河子	新疆石河子市公安局官方微博	58.97	86.68	53.83	54.19	68.04
4	新疆铁路	乌鲁木齐铁路局官方微博	63.94	81.00	47.14	51.89	64.52
5	阿勒泰公安在线	新疆维吾尔自治区阿勒泰地区公安局官方微博	65.44	57.62	69.06	70.90	63.95
6	新疆反邪教	新疆维吾尔自治区防范处理邪教领导小组办公室官方微博	62.44	51.90	64.17	60.95	60.70
7	新疆平安网	新疆平安网官方微博	48.29	66.99	57.78	52.21	55.27
8	新疆消防	新疆消防总队官方微博	55.98	60.89	49.51	39.97	54.40
9	和田网警巡查执法	新疆和田地区公安局网络安全保卫支队官方微博	56.68	61.78	48.83	27.95	53.49
10	昌吉消防支队	新疆昌吉州公安消防支队官方微博	55.71	60.03	45.57	43.96	53.22

Central government rankings of Weibo accounts in Xinjiang Province

Example: 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

Example: Astroturfer Detection

Bureaucrats are often required to follow the account of the bureaucracy at which they are employed/affiliated

章贡区教育局关注“章贡发布”政务微博统计表

序号	学校（单位）	姓名	微博名称	是否已关注
1	赣七中	[illegible]	[illegible]	已关注
2	赣七中	[illegible]	[illegible]	已关注
3	赣七中	[illegible]	[illegible]	已关注
4	赣七中	[illegible]	[illegible]	已关注
5	赣七中	[illegible]	[illegible]	已关注
6	赣州市嵯峨寺小学	[illegible]	[illegible]	已关注

Document from a local propaganda department email leak.

Example: 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 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

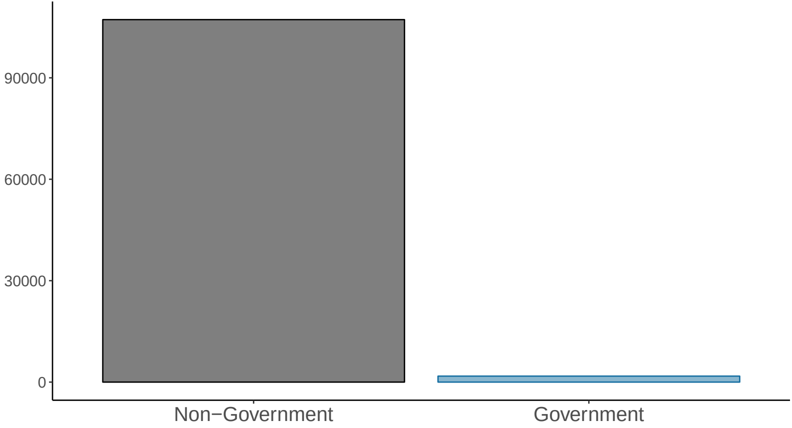
Document from a local propaganda department email leak.

Example: Astroturfer Detection

- 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.

A Motivating Example

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



Example: Astroturfer Detection

Are Weibo accounts

government or **non-government**?

	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: Astroturfer Detection

Model performance (F1): 0.93

Avatars of predicted government accounts.

Tianjin Explosion

Tianjin Explosion: Comment Content

Ordinary Commentary			Astroturfer Commentary		
term	*English translation*	*weight*	*term*	*English translation*	*weight*
爆炸	explosion	0.048	致敬	to pay respects	0.168
捐款	donations	0.047	逝者	the dead	0.158
应该	should	0.038	消防官兵	firefighters	0.133
事故	accident	0.038	安息	rest in peace	0.119
天津	Tianjin	0.025	祈福	to send thoughts	0.108
天津港	Tianjin Port	0.025	天津	Tianjin	0.
安全	safety	0.022	相信	to believe	0.095
政府	government	0.021	希望	hope	0.094
知道	know	0.020	消防	firefighters	0.088
生命	life	0.018	消防员	firefighters	0.082
希望	hope	0.018	英雄	heroes	0.072
责任	responsibility	0.018	加油	to cheer on	0.064
问题	problem	0.017	传谣	to spread rumors	0.062
发生	happen	0.015	默哀	silent tribute	0.060
砖家	“expert” (internet slang)	0.015	政府	government	0.061